# Big Data Analytics Capabilities and Sustainability Performance of Healthcare Supply Chain in Developing Countries: The Mediating Role of Public Procurement Optimisation

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Under the Supervision of

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May 2025

# Certificate of Original Authorship

I, Md Ahsan Uddin Murad, declare that this thesis is submitted in fulfilment of the requirements for the award of PhD in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.
This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Programme.

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## List of Abbreviations and Terminology

BD: Big Data

BDA: Big Data Analytics

BDAC: Big Data Analytics Capabilities

EHR: Electronic Health Record

ABDM: Analytics-Based Decision Making

RBV: Resource Based View

DCV: Dynamic Capability View

SCM: Supply Chain Management

CPTU: Central Procurement and Technical Unit

DGHS: Director General of Health Services

SC: Supply Chain

SCM: Supply Chain Management

SSCM: Sustainable Supply Chain Management

SSC: Sustainable Supply Chain

SSCP: Sustainable Supply Chain Performance

SDG: Sustainable Development Goal

IoT: Internet of Things

WoS: Web of Science

GS: Google Scholars

# Abstract

There is an exponential growth in the creation of data, which is set to reach 175 zettabytes by 2025, surpassing the capabilities of traditional database tools and compelling industries to adopt advanced data analytics. Big Data Analytics Capabilities (BDAC) stems from IT capability, which involves integrating IT-based resources with other organisational resources to create value. BDAC demonstrated its transformative potential across various sectors, including manufacturing and banking, by converting vast amounts of data into actionable insights that enhance decision-making and operational efficiencies. Despite these advancements, the integration of BDAC in healthcare remains under-explored, especially in developing economies such as Bangladesh, where unique regulatory demands and complex stakeholder dynamics pose additional challenges.

This thesis investigates the impact of BDAC on 'sustainability performance' in healthcare supply chains, with a focus on the optimisation of public procurement processes as mediating factors. It addresses a critical gap in the literature through the exploration of the ways BDAC could enhance sustainability in the healthcare supply chain, particularly in the context of a developing country. This study aims to (1) examine the ways BDAC can improve sustainability in healthcare supply chains, (2) evaluate BDAC's influence on sustainability decision-making across economic, social, and environmental dimensions and (3) analyse BDAC's effects on the optimisation of public procurement processes and its subsequent impact on sustainability performance.

Through the employment of positivist paradigm and quantitative research methods, this study utilises surveys to gather 225 empirical data from stakeholders in Bangladesh's healthcare and procurement sectors. The analysis of these data reveals that higher levels of BDAC positively influence sustainability performance in healthcare supply chains, and public procurement optimisation mediates this relationship. This study validates measurement models and offers practical and theoretical insights into BDAC adoption in resource-limited healthcare systems, highlighting its role in advancing sustainability and guiding managers, stakeholders, and policymakers in developing countries. Future research directions include the expansion of this scope to other sectors, exploring alternative mediators, and testing the generalisability of these findings across various developmental contexts.

# Publications

**Journal Paper:**

1. Uddin Murad, Md Ahsan, Dilek Cetindamar, and Subrata Chakraborty. 2022. "Identifying the Key Big Data Analytics Capabilities in Bangladesh's Healthcare Sector" *Sustainability* 14, no. 12: 7077. https://doi.org/10.3390/su14127077

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3. Uddin Murad M.A., Kozanoglu D.C., Chakraborty S. "Public Procurement, Big Data Analytics Capabilities, and Healthcare Supply Chain Sustainability" (2022) Proceedings of the Annual Hawaii International Conference on System Sciences, 2022-January, pp. 296 - 303,

# 1. Introduction

## 1.1 Research Background and Motivation

The exponential growth of global data, projected to hit 175 zettabytes by 2025, outpaced the growing capacity of traditional database-based tools, driving industries to adopt advanced analytics such as 'big data analytics' (BDA) (Rashid et al., 2024; Yang et al., 2024). Thus, the development of essential capabilities for the integration and operationalisation of BDA in organisation-wide business processes is a crucial business pursuit now. In various sectors, BDA Capabilities (BDAC) has proven instrumental in transforming vast amounts of data into actionable insights, enhancing decision-making and operational efficiencies (Venkatesh et al., 2019). BDAC stems from IT capability, which involves integrating IT-based resources with other organisational resources to create value. According to the resource-based view, the value, heterogeneity, and imperfect mobility of IT capability, such as equipment quality, IT skill strength, and learning responsiveness, enable firms to build unique internal resources and gain competitive advantages (Wu et al., 2024). In line with the Dynamic Capabilities View (DCV) theory, BDAC is defined as a firm's capacity to integrate, build, and reconfigure its big data infrastructure, management, and personnel capabilities to enhance strategic decision-making in rapidly changing environments. As a dynamic capability, BDAC plays a critical role in enabling firms to address challenges related to sustainable development, the circular economy, and the big data-driven economy (Said et al., 2023).

Industries ranging from manufacturing to banking have been leveraging BDAC to achieve significant benefits with respect to cost reduction, service innovation, and quality improvement (Aziz et al., 2024; Chen et al., 2020; Dhanasekar*, 2019; Faridoon et al., 2024; León et al., 2024; Wang et al., 2019). In healthcare, despite the development of technological artifacts such as electronic health records (EHR), challenges persist due to complex stakeholder involvement and unique regulatory demands (Benjamin & Potts, 2018; Lintern & Motavalli, 2018; Narattharaksa et al., 2016; Pentrakan et al., 2021). However, successful BDA integration in other sectors highlights its potential benefits, including cost reduction, enhanced services, and improved quality (Pentrakan et al., 2021). Research also confirms that the integration of BDA in a firm improves its sustainability performance (Aziz et al., 2024; Chalmeta & Barqueros-Muñoz, 2021; Del Sarto et al., 2024; Mesquita et al., 2023; Said et al., 2023; Singh & Joshi, 2024; Zhu & Yang, 2021). Yet, research gaps exist in understanding the ways BDAC can

specifically enhance sustainability in healthcare supply chains through the utilisation of optimised public procurement processes, particularly within the context of developing economies like Bangladesh.

This thesis aims to investigate the impact of BDAC on 'sustainability performance' in healthcare supply chains, focusing on the mediating role of public procurement optimisation. The literature review, conducted in this light, underscores three core pillars: BDAC, procurement optimisation, and 'sustainability performance' in healthcare supply chains. Current literature predominantly covers BDAC's effects in developed economies across various sectors, showcasing its transformative potential, which, however, does not include healthcare. Therefore, investigating the impact of BDAC on the 'sustainability performance' of the healthcare supply chain in a developing country's context remains overdue.

While numerous studies confirm that BDA enhances organisational sustainability performance, most existing research has focused on developed economies and private sectors, overlooking the unique dynamics of public healthcare in developing countries. In particular, the role of public procurement—an essential yet often inefficient component in healthcare delivery—has received little attention in the context of BDAC integration. This study is motivated by this gap and seeks to explore how BDAC can be harnessed as a dynamic capability to optimise public procurement processes and thereby enhance sustainability in healthcare supply chains. By addressing this underexplored intersection, the research aims to contribute to both theory and practice, offering context-specific insights for sustainable development in resource-constrained environments like Bangladesh.

### 1.2 Research Questions

To address the gaps that have been identified in the literature with respect to the overarching problem of this research, the following main research questions and sub-questions are formulated to guide this research:

**Main Research Question:**

- How does BDAC enhance the 'sustainability performance' of the healthcare supply chain?
- Does procurement optimisation mediate the impact of BDAC on the 'sustainability performance' of the healthcare supply chain?

**Sub-Questions:**

- How does BDAC facilitate the optimisation of public procurement in healthcare?
- How does the optimisation of public procurement affect the 'sustainability performance' of the healthcare supply chain?

This research aims to produce a managerial lever to improve the 'sustainability performance 'of the public healthcare supply chain. While BDA demonstrated benefits in other sectors, its potential in respect of the enhancement of sustainability in healthcare supply chains, particularly in terms of complexity, volume, and cost optimisation, remains underexplored. This study intends to contribute to this respect through:

1. The exploration of the effects of the integration of emerging technologies into Bangladesh's public healthcare supply chain, focusing on procurement optimisation for sustainability and
2. The examination of organisational capabilities that would be required for successful BDAC integration in Bangladesh's healthcare supply chain, where such capabilities are nascent.

This research seeks to establish the link between BDAC and healthcare public procurement cost optimisation, which is essential for ensuring quality healthcare at affordable prices through optimised sourcing of logistics.

### 1.3 Objectives

The objectives of this research are as follows:

1. **The exploration of BDAC in healthcare supply chains**: Through the investigation of the ways BDAC can enhance sustainability in healthcare supply chains, this research addresses a significant gap in existing literature, which instead, had predominantly focused on BDAC-based applications in manufacturing and retail sectors.
2. **Role of BDAC in the enhancement of sustainability**: The evaluation of BDAC's impact on sustainability decision-making across economic, social, and environmental dimensions within the context of healthcare, which includes the syntheses of fragmented empirical evidence to facilitate the creation of a comprehensive understanding.
3. **Role of BDAC on public procurement optimisation**: The evaluation of BDAC's impact on public procurement optimisation, which includes the exploration of the mediating role of public procurement optimisation to influence the relationship between BDAC and the 'sustainability performance' of the healthcare supply chain.

These objectives collectively aim to advance knowledge on the leveraging effects of BDAC in improving sustainability, efficiency, and responsiveness in healthcare supply chains, with particular emphasis put on diverse and resource-constrained settings.

### 1.4 Research Methods

The research methodology of this thesis outlines a structured approach to investigating the relationship between BDAC and the sustainability performance of healthcare supply chains. This summary highlights key elements of the employed methods of research.

**Research design:** A research design should serve as a blueprint for a study, ensuring the systematic collection and analysis of data in addressing research questions. Besides, as developed in this research, it outlines the chosen methodology—quantitative research through surveys—for the testing of hypotheses effectively. It also addresses the rationale behind data collection methods and strategies, aiming to minimise common method bias.

**Research paradigm:** Positioned within a positivist paradigm, this research emphasises empirical observation and the quantification of data to derive generalisable conclusions. This approach aligns with this study's objective for the exploration of causal relationships and theoretical testing in a real-world context.

**Quantitative research approach:** Utilising surveys as the primary data collection method, the study gathers numerical data from stakeholders involved in the big data and procurement sectors within Bangladesh. The survey employs a Likert scale to measure attitudes and opinions, ensuring a comprehensive understanding of stakeholders' perspectives.

**Research strategy:** The study employs both Systematic Literature Review (SLR) and survey strategies. The SLR identifies gaps and establishes foundational constructs, while the survey method collects empirical data to test hypotheses derived from the literature review.

**Data collection:** Data collection involved a rigorous process of questionnaire development and pilot testing to ensure validity and reliability. This survey targeted stakeholders such as IT managers, procurement officers, and healthcare administrators, ensuring the presence of a diverse sample representing various perspectives.

**Questionnaire design:** The design of the questionnaire focused on clarity, simplicity, and alignment with the objectives of this research, with an aim to mitigate response bias. It underwent multiple revisions on the basis of feedback received from experts and 'pilot testing', which assisted with the refining of questions and ensuring comprehensibility across diverse backgrounds of respondents.

The methodology of this research outlines a systematic approach, which integrates theoretical frameworks with empirical observations through the employment of quantitative methods of research. Through the adoption of a positivist paradigm and the leveraging of survey strategies, this study aims to contribute valuable insights in respect of the integration of BDAC and procurement optimisation to enhance sustainability in healthcare supply chains.

### 1.5 Findings and Implications

**Key Findings:** This study investigates two primary research questions:

1. **Impact of BDAC on 'healthcare supply chain sustainability':** This research confirms that higher levels of BDAC positively influence sustainability performance within the healthcare supply chain of developing countries, in particular Bangladesh. It extends prior research, predominantly conducted within the context of developed countries.
2. **Mediating role of public procurement optimisation:** It is found that public procurement optimisation acts as a mediator between BDAC and the 'sustainability performance' of healthcare supply chain. This finding implies that the optimisation of procurement processes through BDAC enhances overall sustainability outcomes in healthcare settings.

**Theoretical Implications:** This study produces the following theoretical contributions:

- The validation and application of a measurement model for BDAC, procurement optimisation, and sustainability performance in a developing country's context, which fills in a gap present in respect to empirical research.
- The highlighting of unique challenges and opportunities for the implementation of BDAC in developing countries, as distinct from those of the developed economies.

**Managerial Implications:** The findings of this research produce the following contributions with respect to practice:

- A potential for increased confidence among managers in respect of the adoption of advanced analytics such as BDAC in decision-making, particularly in resource-constrained environments.
- The provision of effective guidance for healthcare industries in respect of the prioritisation of specific components of BDAC, and the structuring of implementation strategies to cater for local contexts.

- The creation of insights relating to the minimisation of organisational gaps in respect of BDAC through strategic human capital development and technology-related framing of policies.

**Research Limitations:** The limitations of this study include: its regional focus, i.e., in the context of Bangladesh, potential presence of biases in expert opinions, and the technical nature of instruments of survey, suggesting areas for improvement in future research.

**Future research directions:** Further research could be conducted in the following areas:

- To extend the findings that are produced in this research to other areas of the healthcare supply chain, especially the inclusion of perspectives from the private sector.
- The exploration of alternative mediators and moderators between BDAC and organisational outcomes.
- The test of the generalisability of findings across various developing economies to enhance the applicability and robustness of the produced results.

In conclusion, this research underscores the transformative potential of BDAC in the enhancement of 'sustainability performance' within Bangladesh's healthcare supply chains, offering theoretical insights and practical guidelines for industry-based stakeholders and policymakers.

### 1.6 Thesis Structure

This thesis is structured as follows:

**Chapter 2** introduces the foundational concepts and thoroughly reviews pertinent literature. **Chapter 3** investigates the theoretical background and develops the hypotheses to be tested in this study. **Chapter 4** outlines research methodology, including study design, variables' measurement, and data collection and analysis techniques. **Chapter 5**, then, conducts an analysis of the quantitative data, presenting the outcomes of 'hypothesis testing', while also examining relationships between key variables, including overall, direct, and indirect effects. **Chapter 6** wraps up this study, discussing its contributions to its respective field while also outlining its limitations and providing suggestions for further research.

# 2. Literature Review

## 2.1 Introduction

International Data Corporation (IDC) projected global data volume to hit approximately 175 zettabytes by 2025 (Yang et al., 2024), almost double the size of the data produced in the year 2019 (Rashid et al., 2024). Such an exponential growth of data gave birth to the term 'big data', which could be stated as an accumulation of gigantic volumes of data from numerous sources to reinforce a wide range of types of decision-making (Pham & Vu, 2024). The growing data volume is such immense and complex that it is becoming unmanageable through the use of traditional database tools or applications (Al-Khatib, 2022b; Khan et al., 2024; Rajnoha & Hadac, 2022; D. Zhang et al., 2022). Therefore, firms are continually searching for better tools, such as data analytics, to retrieve useful information from piles of data, popularly known as 'big data' (Atuahene et al., 2022; Huang et al., 2022; Ranjan & Foropon, 2021). To leverage business decision-making through the transformation of unstructured "big data" sets into meaningful information, new computational approaches are being introduced, where Big Data Analytics (BDA) has become a powerful tool for performance enhancement and the creation of organisational competitive advantage (Aziz et al., 2024).

In healthcare, many organisations invested considerable levels of effort in trying to manage extensively voluminous data using innovative technologies such as the introduction of electronic health records (EHR) (Benzidia et al., 2023; Chen et al., 2020; Rai et al., 2024). EHR is considered being a breakthrough in health information management, which utilises BDA as contextual intelligence for the assessment of diseases and the performance of epidemiological analyses (Chen et al., 2020). However, many healthcare organisations embraced early failure in their adoption of EHR despite considerable efforts exerted from their ends in trying to construct successful big data systems. One of the root causes of this failure lies in the requirement for the involvement of multiple stakeholders in technology integration into healthcare; unlike other sectors, where the government often has a central role to play. The complexity and risks associated with the healthcare industry make technology integration uniquely challenging (Benjamin & Potts, 2018). On the other hand, several challenges are still unresolved with respect to the testing and implementation of technological innovation in healthcare, hence, little has been published on associated processes and best practices (Tseng et al., 2018).

For example, the hospital organisational system is complex and has an unpredictable nature of patients' profiles, coupled with an uncontrolled, high demand for on-time care (Yu, Zhao, et al., 2021). In addressing these characteristics, a robust and efficient healthcare supply chain could entail a crucial solution for organisations. It could leave sufficient scope for staff to concentrate on their core activities in improving patients' conditions (Ageron et al., 2018), where effective integration of data analytics into healthcare supply chains is considered to be a game-changer (Chen et al., 2020; Regan, 2022; Yazdani et al., 2020). Also, having appropriate capabilities for the utilisation of BDA is considered being a critical factor for the successful adoption of data analytics by any firm (Benzidia et al., 2023; Faridoon et al., 2024; Huang et al., 2022; Yu, Zhao, et al., 2021).

Data analytics techniques provide business organisations with greater accuracy and insights, which could lead to successful resource-sharing across all 'supply chain'-based entities, irrespective of industry or sector (Hofmann & Rutschmann, 2018). Successful integration of BDA is reported to have brought tangible positive impacts in many sectors. It has also been noted that the integration of BDA into the healthcare supply chain could also produce threefold benefits: reduction of costs, the introduction of new services, and an increase in the quality of service (Chen et al., 2020; Dhanasekar*, 2019; Pentrakan et al., 2021; Wang et al., 2019; Yazdani et al., 2020).

However, mere cost reduction or improved quality of service no longer represent the main objectives of any firm. Firms are internally and externally expected to ensure sustainability, besides the achievement of their business objectives (Allahyarzadeh-Bidgoli & Yanagihara, 2023; Azmi et al., 2022; Beheshtinia et al., 2021; Chalmeta & Barqueros-Muñoz, 2021; Choi, 2022; Dai et al., 2023; Evangelista & Hallikas, 2022; Li et al., 2022; Mishra et al., 2023). On the other hand, many business-oriented functions, both directly and indirectly, contribute to the achievement of sustainability in any business (Azmi et al., 2022; Beier et al., 2017; Boussemart et al., 2020; Choi, 2022; Lavalle et al., 2020; Li et al., 2022; Mengistu & Panizzolo, 2021; Phalake et al., 2023; Wang et al., 2023). Therefore, understanding the roles of business functions in the pursuit of sustainability represents a crucial goal for any firm or sector.

This research envisaged to investigate the impact of two different business capabilities on supply chain sustainability. More specifically, the primary goal of this research is the identification of the manners BDAC could improve the 'sustainability performance' of

healthcare supply chains, besides determining the mediating role of public procurement optimisation (second business capabilities) between 'sustainability performance' and healthcare supply chains. Accordingly, this literature review attempts to explore three core pillars of this research project: (1) BDAC, (2) procurement optimisation and (3) sustainability performance of the healthcare supply chain.

### 2.2 Systematic Literature Review

Authors are most likely to demonstrate interest in past publications that are the most receptive and include recent developments in the pertinent field (Poeppelbuss et al., 2011); hence, an excellent literature review facilitates future researchers to publish new research in the relevant area (Berger et al., 2014). It would also answer future researchers' quest in respect of areas of research that have already been addressed, revealing a research gap that could potentially be pursued. A well-prepared literature review is particularly crucial as it connects proposed research to prior research by showing the originality and relevance of the identified problem, thus distinguishing the proposed study from the remaining works. Besides, it also showcases a researcher's preparedness to pursue the proposed research (Poeppelbuss et al., 2011).

A systematic literature review (SLR) has been conducted to identify the existing works on all key concepts pertinent to this research project. Emphasis was given to three core pillars of the research investigation: BDAC, procurement optimisation, and sustainable healthcare supply chain. This literature review focused on analysing articles published in the broad area of applicability of BDAC on supply chain process, seeing through a sustainability mirror. To further narrow down the scope, papers related to BDAC in the roles of either input/output or mediator/moderators were analysed and synthesised to identify the outcomes of current research as well as research gaps needing to be addressed in future research.

### 2.3 Methodology Applied for SLR

A literature survey has been conducted to explore developments in this area over the past ten years. Based on the mostly used PRISMA SLR article screen methods (Moher et al., 2009), the following analyses were made for this review.

- The existing literature analysis on BDA in healthcare supply chain from the three richest research depositories of the world, Web of Science (WoS), Scopus and Google Scholars (GS), to locate current works in this field and identify future research trajectory.

- Efforts were made to synthesise the existing articles to identify the most prevalent and rare areas of research from within the list of papers that were sorted out from search results.
- All research papers were ranked on the basis of a quality rubric, explained in the later section. The top articles were analysed further to obtain a glimpse of this sector.
- Summarised the findings of the identified papers to discover key determinants and success factors in relation to BDA integration.
- Emerging technologies and BDA in the areas related to healthcare supply chain, as well as in the field of digital transformation, are outlined. The impact of new technology and organisational measures required to embrace new technology are also explained.

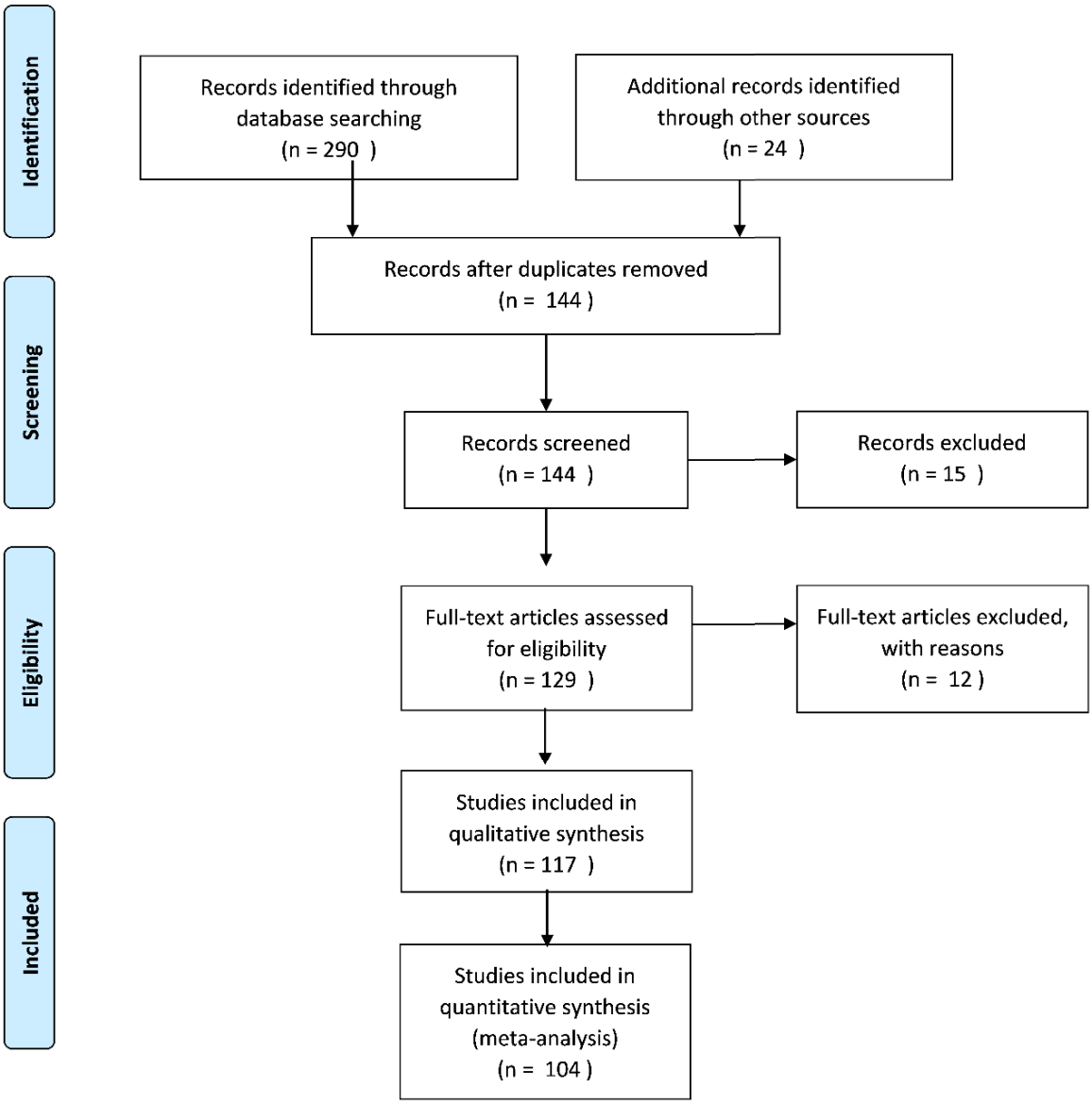



Figure 2.1 PRISMA Diagram that was followed for SLR

## 2.4 Search Protocol

A comprehensive analysis of an area of research consists of a systemic structured review (Bandara et al., 2011), an exhaustive literature search strategy with a selection of the most relevant publication outlets, publication period, and proper keywords (Brocke et al., 2009). Two fundamental steps, suggested by Bandara et al. (Bandara et al., 2011) and echoed by others (Cooper, 1988; Webster & Watson, 2002), and (Levy & Ellis, 2006) are currently widely being followed. These two steps are: (i) selecting highly relevant sources for search, and (ii) defining search rules by considering search terms, time frames, and search fields.

These two steps have been followed in the literature search process for this research. A pilot search of journals and research papers was conducted on 10 January 2021 and was later updated on 05 September 2024. Efforts were made to locate works of high quality within the field of big data technology with respect to the healthcare supply chain. According to Webster & Watson (Webster & Watson, 2002), a literature review should include only the leading journals that have established a fame of quality and are most likely to contain significant contributions to the concerned field. One useful way to identify high-quality journals or conference papers is through the consideration of their journal rankings (Brocke et al., 2009).

Overlapping indexed articles in various databases are a challenge during database searches in a literature review. The overlapping of indexed articles across various research outlets is a long-contested issue, too. A study by Gavel & Iselid (Gavel & Iselid, 2008) found that 84% of the WoS titles are also indexed in Scopus, while 54% of the Scopus titles are also indexed in WoS. On the other hand, areas of scientific research also need to be structurally standardised in different research outlets, such as WOS and Scopus. Therefore, a separate analysis is required for a more accurate review of a field (Pihir et al., 2019). Journal articles that have been indexed in databases since 2010 are considered for this literature review. Articles that have been accepted for publication in 2024 issues, but are indexed in these databases, are also included. For contemporary agendas in research, it is recommended to keep a search span of at least ten years; otherwise, it can severely limit the incorporation of eligible studies for review (Meline, 2006).

Table 2.1 Search criteria and counts of articles retrieved

| **Features** | **Big Data Analytics Capability** | **Procurement Optimisation** | **Sustainable Supply Chain Performance in Healthcare** |
|---|---|---|---|
| Research Question: | Does BDAC improve the sustainability of the healthcare supply chain? | Does procurement optimisation have a mediating role between BDAC and a sustainable healthcare supply chain? | Does BDAC improve the sustainability performance of the healthcare supply chain? |
| Search Criteria | ALL ( *bda* OR *bdac* AND *capabilit** AND *"Big Data"* ) AND PUBYEAR > *2010* AND ( LIMIT-TO ( DOCTYPE , *"ar"* ) ) AND ( LIMIT-TO ( LANGUAGE , *"English"* ) ) | TITLE-ABS-KEY (procurement AND "Big Data" AND opti* ) AND PUBYEAR > 2010 AND ( LIMIT-TO ( DOCTYPE , "ar" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) ) | (ALL ( *sustainable* OR *sustainability* ) AND PUBYEAR > *2010* ) AND ( ( ( ( *"supply chain"* ) ) AND ( *"big data"* ) ) AND ( *"performance"* ) ) AND ( *bda* ) AND ( LIMIT-TO ( DOCTYPE , *"ar"* ) ) AND ( LIMIT-TO ( LANGUAGE , *"English"* ) ) |
| Article retrieved | Scopus (200), WoS (221), GS (238) | Scopus (15), WoS(17), GS (16) | Scopus (119), WoS (116), GS (122) |
| after first screening | 123 | 49 | 118 |
| | *after removing duplication (after initial screening by reading title only) | | |
| after second screening | 87 | 13 | 44 |
| | **after abstract analysis (after full-text analysis) | | |
| after final screening | | **104** | |

## 2.5 Quality Assessment

Quality assessment works as a gatekeeper to scrutinise the accuracy and reliability of selected articles. There is a prevalent tendency to mix any analytics, such as BDA and digital transformation, with digitisation or mere automation. It, therefore, is particularly essential to rigorously conduct the quality test of any established quality assessment framework. A quality rubric introduced by (Mullet et al., 2017) is utilised to evaluate the quality of each article. This rubric examines research articles on seven criteria, including Objectives, Literature review, Theoretical framework, Study participants, Methodology used, Results and discussion, and Significance of the study. Each component of the quality rubric was measured on a scale of zero to three where 0= Below standard, 1=Near to standard, 2= Standard, and 3= Exceeds standard. The total score of each article was calculated by summing scores from all seven components; hence, the overall rating for each item would fall between zero to twenty-one.

Articles that scored less than twelve on that scale were excluded from further analysis. By applying both the search criteria and quality assessment rubric, 104 articles were retained, and the remaining articles were excluded. Although it was attempted to evaluate these articles by using a standard manner, the exclusion of bias is not guaranteed. Usually, the inclusion of a second author works as a guard against bias to thoroughly check the included and excluded articles in a literature review.

Table 2.2 Rubric of quality assessment

| Criteria | 3=Exceeds standard | 2= Standard | 1=Near to standard | 0=Below standard |
|---|---|---|---|---|
| Objectives | Objectives or purposes, research questions, hypotheses (if any), rationale, and key terminologies are clearly articulated. | Objectives or purposes, research questions, hypotheses (if any), rationale, and key terminologies are adequately articulated. | Neither defined nor discussed. In some cases, it is defined very poorly. | It is not possible to determine the purpose. |
| Literature Review | Comprehensively studied previous work and connected compellingly. Positioned the topic within the broader field. The research gap(s) has been articulately identified, and new perspectives have been offered. | Comprehensively studied previous work and connected compellingly. Discussed what has been covered and what has not. The research gap has been identified adequately. | Examined the topic minimally. Make a poor connection to the previous work. Positioned the problem vaguely with the broader area. Identified the research gap but not convincingly. | The article merely discusses what has been done only and fails to connect with previous work. Lack of logical organisation of the article. The research gap has not been identified. |
| Theoretical Framework | Frameworks aligned with the study are identified with justification and articulated. The choices of the framework are discussed and justified. | Frameworks are identified and discussed, and choices are explained. However, the justification of alignment has not been provided. | Frameworks are mostly implied or vaguely explained. Neither justification of alignment is provided nor can be inferred from. | A description of frameworks is absent, let alone a justification of alignments. |
| Study participants | Sample selection, sample size, Context, and biases in selection are explained with detailed contextual explanation. | Sample selection, sample size, and selection bias with explained without contextual explanation. | A basic description of the sample, sample size, and sampling procedure are provided. | An incomplete description fails to explain the sampling procedure. |

| | | | | |
|---|---|---|---|---|
| Method | The procedure, instruments, and their administration mechanism are articulately described, and potential bias is also discussed. Methodological decisions are supported with best practice examples. Evidence for validity and reliability is provided. | The procedure, instruments, and their administration mechanism are described, and potential bias is also discussed. Evidence for validity and reliability is provided. | Procedure and instrument described. Evidence for validity and reliability is insufficient. | The procedure and instrument are described without details. Evidence for validity and reliability is absent. |
| Result and Discussion | The detailed result with exceptional use of data displays (synthesis or visualisation). A connection with findings and past work, including the direction to future research exits. Conclusions articulately cover the problem or questions. | The complete result with the traditional use of data displays (Table, charts). A connection with findings and past work, including the direction to future research exits. Conclusions articulately cover the problem or questions. | Basic results are achieved through traditional data displays (Tables, charts). A connection between findings and past work, including the direction to future research, is missing. Conclusions articulately cover the problem or questions. | A connection between findings and past work, including a direction for future research, is missing. Conclusions do not cover the problem or questions. |
| Significance of the Study | Clearly, convincingly articulates the cross-disciplinary scholarly and practical significance of the study. | It articulates significance within the field only. | Articulates significance within the field but is neither convincing nor clear. | Articulation on the significance of the study is absent. |

Source: (Mullet et al., 2017)

## 2.6. An Overview of the BDAC Literature

### 2.6.1 Big data

In modern days, heterogeneous sources generate massive data quickly and in various formats, which is often referred to as 'big data' (BD). BD is popularly characterised by Vs features, such as volume, velocity, variety, veracity and value (Ducange et al., 2020). BD is considered being an information-based asset that is characterised by a high volume, velocity, and variety that requires specific technology and analytical methods for value to be generated (De Mauro et al., 2016; Vitari & Raguseo, 2019). Although BD may appear to represent a large volume of data, it, in fact, is more than merely the size of the data. A broadly accepted definition of BD is that

the BD paradigm is close to the base of five ‘V’s, namely Volume, Velocity, Variety, Veracity, and Value (Chehbi-Gamoura et al., 2019). The fifth V, which stands for value, refers to the amount of useful knowledge generated by data (Fosso Wamba & Akter, 2015).

Volume refers to vast quantities of data representing exponential growth, which challenges the existing storage devices (Philip Chen & Zhang, 2014). Variety refers to multidimensional data fields, such as handheld devices, IoT, social media, etc. Data variety is merely not limited to system-generated data. Data variety also refers to all types of data generated by humans and machines, including structured and unstructured data (Lyons & Grable, 2018). Velocity refers to the speed of data acquisition and delivery (Gunasekaran, Papadopoulos, et al., 2017), while veracity emphasises data quality and trustworthiness, considering diverse data sources. Veracity, thus, emphasises the importance of data quality and level of trust owing to the presence of many data sources (Akter & Wamba, 2017). While velocity refers to the speed of the generation of data, veracity indicates the trustworthiness of that data, more precisely, the noise and abnormality level in the generated data to decide the levels at which those data could be trusted in decision-making (Moreno-Carriles, 2018; Siewert, 2013). The final V, coined later in addition to ‘4 Vs’, refers to the unfolding of unexploited or underexploited values from BD to support decision-making.

From a theoretical perspective, BD has a similar positioning. In a resource-based view (RBV), the five Vs dimensions of big data mean that big datasets are rare, inimitable, non-substitutable valuable information resources characterised by their high Volume, high Velocity, high Variety, and uncertain Veracity (Vitari & Raguseo, 2019).

The definition of BD is not restricted to any quantifiable data size. Instead, it is characterised by these Vs. If we want to visualise the gigantic data size of today's internet community and the speed of data generation, we can look at recent statistics. As of April 2023, the global count of internet users reached a new high of 5.18 billion, which accounts for approximately 65% of the world's population (Godard et al., 2024; Ramamoorthy et al., 2024). This figure is more than double from counts of internet users reported in 2019 (Khan & Alqahtani, 2020). This implies that big data is expected to keep growing in size.

### 2.6.2 Big data analytics

Firms enjoy a competitive edge if they can enjoy greater success than competitors and have more capability in generating more business value from BD (Wang et al., 2018). Many Supply Chain (SC) stakeholders predict that BD will have a phenomenal impact on supply chain operations, enabling a business manager to make strategic, data-oriented, and informed decisions (Addo-Tenkorang & Helo, 2016). The growing interest in BD has led organisations to integrate appropriate analytics for analysing BD into their supply chain (Dubey, Gunasekaran, & Childe, 2019). These analytics, popularly known as BDA, enable firms to obtain helpful information that allows supply chain executives to estimate better and predict unseen patterns to gain competitiveness in business (Lamba & Singh, 2018). RBV explains how any cutting-edge BDA solutions facilitate the creation of a competitive edge for a firm (Wamba et al., 2017). The resource-based theory (RBT) sees BDA as a resource for any firm, enabling them with strategic technological leverage to outshine competitors (Aziz et al., 2023; Faridoon et al., 2024; Khan & Fatima, 2024; Li et al., 2023; Morimura & Sakagawa, 2023; Syafrizal et al., 2023).

The existing literature relating to BDA and supply chain shows increasing trends in the use of many derived benefits from BD. However, a remarkable difference exists in the definition of BD and its aspects. For example, Lamba & Singh described BD as massive multidimensional data records beyond the capacity of existing tools for analysis (Lamba & Singh, 2018) . Several studies on supply chain emphasise the business value creation of BD irrespective of its origin, quantity, or size (Amit & Han, 2018; Ji-fan Ren et al., 2016). Business value in this context suggests meaningful mining of information by analysing the collected data, and here, the BDA terminology becomes relevant (Gunasekaran, Papadopoulos, et al., 2017; Gunasekaran, Yusuf, et al., 2017). Since the introduction of BDA terminology, it has increasingly become a centrepiece of relevant research. Researchers opined that BDA is the next big thing to handle (Tonidandel et al., 2016), which will process substantial data to convert it into meaningful information (Dubey, Gunasekaran, & Childe, 2019; Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Dubey, Gunasekaran, Childe, Roubaud, et al., 2019). BDA combines predictive methods, statistics, artificial intelligence, and data mining, among many other elements, which make it a powerful, advanced analytic approach to processing voluminous, unstructured datasets (Popovic et al., 2018).

Decision-making in an organisation is a multidisciplinary action involving economics, philosophy, psychology, mathematics, management, etc. Decision-making is not a clear-cut process; however, research suggests that BDA creates competitive advantages by helping improve decision-making processes (Faridoon et al., 2024; Hamzeh & Aburub, 2024; Khan & Fatima, 2024; Mishra et al., 2023; Shan & Luo, 2024; Siciliani et al., 2023; Talib et al., 2023; Zareravasan & Ashrafi, 2019). Some early studies found that those business organisations that focused on structured adoption of BDA in their decision-making processes reported performance gains (Birkel et al., 2019; Gupta & George, 2016; Hassna & Lowry, 2018; Wamba et al., 2017). In this line of thought, some other studies espoused the idea of cultivating analytics-based decision-making in business process innovation in organisations (Bouncken et al., 2016; Liu et al., 2018).

Research also cautioned firms that appropriate organisational capacity to manage BDA projects is paramount in leveraging the power of BDA. Organisational success in managing the BDA project investment (Birkel et al., 2019) and reliance on analytics-based insights in decision-making are crucial in gaining a competitive advantage (Akter, Gunasekaran, et al., 2020; Akter, Motamarri, et al., 2020). However, an industry report predicts that 80% of data and analytics (D&A) initiatives would fail by 2027 (Inc, 2024). A sizeable count of organisations could still not realise the innovation processes through BDA investment (Günther et al., 2017), which prevents these organisations from inculcating Analytics-Based Decision Making (ABDM). Therefore, the adoption of organisation-specific, appropriate BDA capabilities is essential in yielding expected returns from BDA integration. Capitalising on the organisation-wide BDA impact can allow firms to focus on many areas with a higher importance in business process innovation, as ABDM could take care of many core issues in business (Mikalef & Krogstie, 2020). Where possible, integrating ABDM practices in every stage of the decision-making process can ensure optimum economic return on business functions. In an age of technological sophistication, managers should rely more on analytics-based decisions as BDA integrates a high volume of structured and unstructured data while reducing uncertainty (Turban et al., 2015).

### 2.6.3 Basic types of analytics and BDA sophistication

Intelligent BDA tools appear to be a source of competitive advantage, and an increasing number of firms are leveraging BDA by controlling and analysing a large volume of data (Mariani & Fosso Wamba, 2020). A range of BDA tools is available due to the variety in functionality,

scope, and sophistication. BDA tools are classified into various categories by different researchers in congruence with their level of complexity. There are three types of analytics: descriptive, predictive, and prescriptive.

Descriptive analytics tries to improve the existing systems and techniques by modelling historical data and behavioural patterns (Wang et al., 2016). Through an analysis of past trends and exceptions, descriptive analytics alerts decision-makers by visualising results in an understandable format (Varela Rozados & Tjahjono, 2014).

Through the use of machine learning and data mining techniques, predictive analytics predicts future trends from current and historical 'data patterns' (Assunção et al., 2015). In respect of supply chains, predictive analytics utilise qualitative and quantitative approaches to predict the past and future levels of busing process integration in supply chain design. It utilises various mathematical tools such as time series analysis, advanced forecasting methods, regression analysis, etc. (Varela Rozados & Tjahjono, 2014).

Prescription analytics is a particular form of predictive analytics that proposes future actions either to benefit from future events or to avoid risk. Optimisation, simulations, or similar techniques are utilised in the adoption of this type of analytics. Among all three types of analytics, prescriptive analytics is the least prevalent in organisations, as it still needs to pass the trustworthiness test of many organisations (Deshpande, 2019; Heidari, 2018).

An organisation's BDAC level defines its success by leveraging different tools. Turban et al. classified BDA tools into three categories (Turban et al., 2015), whereas Chawda and Thakur BDA tools are categorised into five categories (Chawda & Thakur, 2016): discovery tools, business intelligence (BI) tools, in-database analytics, high-availability distributed object-oriented platform (Hadoop), and decision management.

Different categories have different levels of sophistication frameworks, and different BDAC levels are required to yield potential benefits from using BDA. The sophistication of BDA tools provides a competitive advantage in decision-making. Accordingly, in consideration of an organisation's BDAC, different organisations or sectors utilise the power of different types of BDA tools. Unlike traditional analytic tools, BDA tools utilise machine learning (Agarwal et al., 2020; Ibrahim et al., 2023; Kusonkhum et al., 2023), while sophisticated BDA tools highly

impact the quality and accuracy of predictions and decisions (Andiola et al., 2020; Liu & Vasarhelyi, 2014). The BDA sophistication level varies from basic mathematical data interpolation to advanced analytical methods and tools. This range starts with simple spreadsheets and then gradually moves into more sophisticated tools such as BI, statistical packages, data mining suites, data visualisation, and high-performance computing tools.

Since its emergence, BDA has continued to grow with more sophistication to support organisational decision-making processes in various complicated situations (Liu & Vasarhelyi, 2014). It is almost inarguably established that BDA converts big data into ready-to-deploy business intelligence for organisations. Hence, a better BDA tool leads to better data insights and better decision-making (Venkatesh et al., 2019).

The primary function of BDA is to understand trends and patterns by gathering in-depth insights from a big dataset. This process commences through the collection of data from multiple sources and then injecting it into distributed databases after the raw data is cleansed (Chauhan et al., 2020). Valuable insights from those databases are, then, retrieved as input for data analytics, known as data mining. In healthcare, a four-layered data tool is suitable for the analysis of healthcare data, where different tools and methods are utilised in each layer (Chauhan et al., 2020; Dhanasekar*, 2019). For example, tools such as Sqoop, Fumes, and Storm are utilised in the task of data injection. Tools such as RapidMiner are utilised for data extraction and analysis, where various data manipulation tools like Hive, Pig, MapReduce, and Spark are popularly utilised. Data collected from various sources requires cleansing before it can be processed. Tools such as Sqoop and Flume are utilised in this end. Hence, it is implied that organisations utilise different BDA tools for different frameworks and layers to make their BDA sophisticated and meet business needs. The more sophisticated the BDA tools, the more usable and accurate decisions can be derived, which could drive the creation of more value in business.

### 2.6.4 Big data analytics capabilities

Research on big data analytics has predominantly concentrated on the significance of big data analytics capabilities, though the concept is relatively new, and there is no established consensus regarding its precise definition. From a strategic viewpoint, some scholars describe it as the ability to leverage big data for decision-making that influences an organisation's operational strategy (Xing et al., 2022). BDAC refers to an organisation's ability to process, visualise, and analyse data to generate insights that drive data-informed decision-making,

planning, and execution. When effectively developed and implemented, BDAC enables businesses to identify valuable information, reveal hidden patterns, detect market trends, and uncover previously unknown correlations (Zhao et al., 2024).

BDAC enables an organisation to convert big data into ready-to-deploy business intelligence for organisations. Therefore, a better BDA tool and the ability to run that tool lead to better data insights and better decision-making (Venkatesh et al., 2019). Current BDAC research predominantly utilises contexts of developed economies, while very few investigations have insofar been carried out in the healthcare sector, as seen in Appendix A's summary table.

Zan et al. identify two key issues in the literature that hinder the understanding of how BDAC drives innovation (Zan et al., 2024). Firstly, there is a significant shortage of empirical studies that uncover specific mechanisms through which BDAC influences innovation by a firm. While various studies examined BDAC's outcomes, most focused predominantly on firms' performances. My findings also reveal the literature's indication of the value-creation process of BDAC, mainly centring on the viewpoint of dynamic capabilities [Appendix A]. However, the lack of a consistent definition and integration of dynamic capabilities posed challenges to the advancement of empirical research (Zan et al., 2024). Although the number of studies is comparatively low, the impact of BDAC on 'sustainability performance' has been studied in various contexts. These studies range from the supply chain's sustainable performance to the sustainability of innovation. All studies that were retrieved from our search protocol discussed sustainability as an output, as presented in Table 2.3. Table 2.3 includes studies relating to sustainability from various perspectives, such as sustainable environmental performance (Bader Khamis AlNuaimi et al., 2021; Belhadi et al., 2020; Sahoo et al., 2023); Green Supplier Integration (Y. Liu et al., 2022), Green Customer Integration (Y. Liu et al., 2022). The number of studies reflecting sustainability from all three dimensions and the supply chain context is very low.

Table 2.3 Summary of studies with BDAC (Input) and sustainability (Output)

| BADC as Input | Mediator or Moderator | Sustainability as Output |
|---|---|---|
| (Song et al., 2020), (Zhang et al., 2020), (Ciampi et al., 2021), (Lozada et al., 2023), (Munodawafa & Johl, 2019), (Liu & Mehandjiev, 2020), (Upadhyay & Kumar, 2020), (Yasmin et al., 2020), (Akter et al., 2016), | Entrepreneurial orientation (Ciampi et al., 2021; Tipu & Fantazy, 2023), Data Driven Culture (Shamim et al., 2020) Digital Dynamic Capability (Liu & Mehandjiev, 2020), organisational culture and internal analytical knowledge (Upadhyay & Kumar, 2020), Analytics Capability Business Strategy Alignment (Akter et al., 2016), Information Governance, Environmental Uncertainty (Mikalef, Boura, et al., 2020), Dynamic Capabilities | Sustainable Innovativeness (Song et al., 2020), Success of Sustainability Development Project (Zhang et al., 2020), Supply Chain Sustainability (Shokouhyar et al., 2020), Sustainability-Air pollution |

| | | |
|---|---|---|
| (Mikalef, Boura, et al., 2020), (Mikalef et al., 2019b), (Ferraris et al., 2019), (Hooi et al., 2018), (Dubey, Gunasekaran, Childe, Roubaud, et al., 2019), (Shokouhyar et al., 2020), (D. Zhang et al., 2019), (Ramadan et al., 2020), (Hao et al., 2019), (Jha et al., 2020), (Xiao et al., 2020), (Ashaari et al., 2020), (Rialti et al., 2019), (Wamba et al., 2017), (Mikalef et al., 2019b), (Arunachalam et al., 2018), (Belhadi et al., 2020), (Mandal, 2018, 2019) (BDA Management Capability), (Behl, 2020b) (BDA Management Capability and BDA Talent Capability), (Wang & Hajli, 2017), (Dubey, Gunasekaran, & Childe, 2019; Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Dubey, Gunasekaran, Childe, Roubaud, et al., 2019), (Jeble et al., 2018) (Big Data and Predictive Capability), (Srimarut & Mekhum, 2020), (Behl et al., 2022; Gupta & George, 2016), (Tipu & Fantazy, 2023), (Shi et al., 2023), (Al-Khatib, 2022b), (Gupta et al., 2023), (Y. Liu et al., 2022), (Makhloufi, 2023), (Aziz et al., 2024), (Li et al., 2023),<br><br>BD Technological Capabilities (Jum'a et al., 2023), BD Personal Capabilities (Jum'a et al., 2023), (Fantazy & Tipu, 2023), (Arshad et al., 2022), (Mesquita et al., 2023), (Said et al., 2023), (Sahoo et al., 2023) | (Gupta et al., 2023; Mikalef et al., 2019b; Mikalef, Krogstie, et al., 2020; Xiao et al., 2020), Environment (Dynamism, Heterogeneity, Hostility), Knowledge Management (Ferraris et al., 2019)), Organisational Flexibility (Dubey et al., 2018; Dubey, Gunasekaran, Childe, Roubaud, et al., 2019), Innovation Capability, Data Availability (Ramadan et al., 2020), Digital Platform Capabilities, Environmental Dynamism (Xiao et al., 2020), Continuous Process Innovation (Ashaari et al., 2020), Organisation information management system-Fit, Organisational Resistance information management Organisational Agility, organisational ambidexterity (Rialti et al., 2019), Process Oriented Dynamic Capability (Wamba et al., 2017), GM Practice, LSS Effort (Belhadi et al., 2020), Competitive Advantage, Organisational Culture, Innovation (Behl, 2020b) Innovative Green Product Development, Employee Development, Innovation and learning performance, Supply Chain Innovativeness (Bag et al., 2021b; Bag, Wood, Xu, et al., 2020; Li et al., 2023), Developmental Culture (Lin & Kunnathur, 2019) Big Data Analytics Components, Benefit Dimension (Wang & Hajli, 2017), Swift Trust, Flexible Orientation, Control Orientation (Dubey, Gunasekaran, Childe, Roubaud, et al., 2019)), Supply Chain Complexity (Jeble et al., 2018) BDAC Technical Capability and Human Capability (Bader Khamis AlNuaimi et al., 2021), Supply Chain Coordination, Swift Trust, Supply Chain Risk (Behl et al., 2022)), Supply Chain Visibility (Shi et al., 2023), Green Supply Chain Innovation (Al-Khatib, 2022b), Green Incremental Supply Chain Innovation (Al-Khatib, 2022b), Green Internal Integration (Y. Liu et al., 2022), Knowledge Sharing (Makhloufi, 2023), Green Organisational Ambidexterity (Makhloufi, 2023), Green Absorptive Capacity (Makhloufi, 2023), Supply Chain Innovation Capabilities (Jum'a et al., 2023) , Green Supply Chain Performances (Li et al., 2023), Green Dynamic Capabilities (Li et al., 2023) , Knowledge Acquisition (Fantazy & Tipu, 2023), Information Distribution (Fantazy & Tipu, 2023), Shared Meaning (Fantazy & Tipu, 2023), Achieved Memory (Fantazy & Tipu, 2023), Autonomous R&D (Arshad et al., 2022), Absorptive Capacity (Arshad et al., 2022), Lean Technical Practices (Mesquita et al., 2023), Lean Social Practices (Mesquita et al., 2023), Tone at the top (Said et al., 2023), Resource Commitment (Sahoo et al., 2023), Circular Economy Practices (Sahoo et al., 2023) | Management (D. Zhang et al., 2019), Sustainable Competitive Advantage (Ramadan et al., 2020), Sustainability of Innovation and Organisational Development (Hao et al., 2019), Environmental Performance (Bader Khamis AlNuaimi et al., 2021; Belhadi et al., 2020; Sahoo et al., 2023), Sustainable Supply Chain Performance (Bag, Wood, Xu, et al., 2020; Fantazy & Tipu, 2023; Jum'a et al., 2023; Tipu & Fantazy, 2023), Sustainable Supply Chain Performance (Gupta et al., 2023; Jeble et al., 2018), Sustainable Competitive Advantage (Behl et al., 2022), Green Supply Chain Integration (Shi et al., 2023), Green Supply Chain Performance (Al-Khatib, 2022b; Gupta et al., 2023), Green Supplier Integration (Y. Liu et al., 2022), Green Customer Integration (Y. Liu et al., 2022), Green Entrepreneurship Orientation (Makhloufi, 2023), Eco-innovation (Makhloufi, 2023), Sustainability Performance (Aziz et al., 2024; Li et al., 2023; Mesquita et al., 2023), Sustainable Organisational Development (Arshad et al., 2022), Sustainability reporting disclosure on Facebook (Said et al., 2023) |

A comprehensive table with all articles that discussed BDAC is appended in Appendix A to provide a pictorial idea of the scope of the existing BDAC literature.

## 2.7 Overview of Literature Review on Procurement Optimisation

### 2.7.1 Procurement and procurement optimisation

Procurement is the interpretation and arrangement of consumers' needs and prerequisites extended through securing the right commodities/services at the right time and at the right price (Joseph Jerome et al., 2021). Procurement, one of the sources of a firm's competitive advantage, acts as the gatekeeper and undertakes the supply chain's boundary-spanning function for any firm (Liu et al., 2020). Being one of the most important parts of any business's supply chain, the function of procurement contributes directly or indirectly to a firm's performance, therefore, entailing strategic importance (Charpin et al., 2021). In the demonstrated cases of success by global companies, procurement played a significant role; hence, fluctuation of supplies/commodities heavily impacts the management of operational costs (Wang et al., 2022).

The ways companies handle their supply chains in a fiercely competitive and constantly evolving technology-driven business world play a major role in defining the firm's long-term growth and success (Joseph Jerome et al., 2021). It could be commented in this respect that business optimisation has now emerged as a key factor in the sustainability of businesses at a global level. Therefore, a business must ensure supply chain optimisation in its day-to-day activities (Telukdarie et al., 2018). Under the two main uncertain faces of business, i.e. supply and demand, procurement strategies must be aligned in such a way that it is optimised to become a catalyst in meeting all customer demands, thus ensuring the use of optimal business resources (Caniato et al., 2020). Therefore, procurement optimisation is pivotal in making any firm successful in the long run. Recent investigations carried out in this line of thought also support this claim. A firm's success largely depends on the way it manages its procurement and logistics flow on a closed-loop principle (Bag, Wood, Mangla, & Luthra, 2020). Thus, the importance of procurement optimisation in overall supply chain optimisation is paramount to achieving a competitive advantage (Adlane & Aouane, 2020; Arve & Zwart, 2023; Lopomo et al., 2023).

In public sector procurement, this importance is even more significant owing to the scarcity of public resources versus limitless expectations of citizens from their government (Andrade et

al., 2024; Anin et al., 2022; García-Segura et al., 2020; Karttunen et al., 2024). Public procurement is undoubtedly one of the vital economic activities that are carried out within a government's jurisdiction and competence to increase the delivery of welfare to the masses (Maria et al., 2021). The public procurement market is large enough to affect nearly every citizen and organisation (Soylu, Corcho, Elvesæter, Badenes-Olmedo, Blount, et al., 2022). Therefore, the importance of the realisation of optimal value through public procurement is pivotal for every government's success, as a significant component of any country's GDP accounts for public procurement. For instance, in the European Union (EU), approximately 16% of GDP is represented by public procurement (Plaček, Nemec, Ochrana, Půček, & Schmidt, 2019). Thus, it can be uncontestably said that public procurement can significantly impact any country's overall GDP. Hence, the benefits of public procurement optimisation are enormous.\

Public Procurement Optimisation (PPO) refers to the strategic improvement of procurement processes in public sector organisations to achieve greater efficiency, cost-effectiveness, and transparency. This involves utilising technology, data analytics, and best practices to streamline procurement operations, reduce waste, and ensure that public funds are spent responsibly while meeting the needs of the public sector.

### 2.7.2 Procurement and supply chain

As a core business function, procurement is vital in every supply chain to generate business value (Barrad et al., 2020). Hence, low-cost sourcing can significantly help to attain a firm's competitive advantage by making the supply chain cost-effective. Thus, transforming procurement to reduce business costs is no longer a novelty in today's cut-throat, competitive business environment (Barrad et al., 2020). This literature survey confirmed that optimising the procurement process makes the supply chain cost-effective and sustainable by minimising excess consumption of scarce natural resources and reducing waste generation (Bader Khamis AlNuaimi et al., 2021; Arve & Zwart, 2023; Faisal Obaid & Ali, 2022; Mircea et al., 2022; Palander & Vesa, 2022; Schroeder et al., 2018). However, the literature also reveals that procurement in the public sector is less emphasised than that of the private sector and is a relatively new field of scholarly contributions (L. Chen, 2022; Decarolis & Giorgiantonio, 2022; Falcón-Cortés et al., 2022; Mahapatra & Mahanty, 2021; Mircea et al., 2022; Mwesiumo et al., 2021; Pentrakan et al., 2021; Soylu, Corcho, Elvesæter, Badenes-Olmedo, Blount, et al., 2022; Soylu, Corcho, Elvesæter, Badenes-Olmedo, Yedro-Martínez, et al., 2022; Yan & Cao,

2022). An increasing count of articles have been published in the area, but the growing interest has yet to form any generally accepted public procurement theories (Koala & Steinfeld, 2018).

Global competition does no longer exists between firms; instead, it exists among supply chains (Ha et al., 2017). Hence, supply chain executives are continually striving to find a way to optimise different supply chain functions to make the whole supply chain process cost-effective. The supply chain is a system or process with at least two entities, but usually more than two, such as suppliers, manufacturers, carriers, retailers, and consumers. It usually is comprised of a series of processes involving its entities in the cycle of production to the distribution of goods or services. Managing all of those processes and entities is called supply chain management (SCM), and since 2000, most SCM has been a cross-functional and cross-enterprise process (Wen et al., 2019). Optimising the procurement process of any supply chain positively impacts the whole supply chain (Adlane & Aouane, 2020; Liu et al., 2023; Pan, 2015). However, this literature survey reveals that such findings were not confirmed in the context of healthcare public procurement in a developing country. On the other hand, the supply chain of the service and manufacturing sectors has some distinct features despite many commonalities. On top of that, in a given supply chain, any supply chain function can be varied from one sub-sector to another. So, a separate sector or context-specific study could only confirm the same applicability of the earlier findings.

### 2.7.3 Role of BDA in procurement optimisation

Over the past several decades, BD has influenced the procurement process, a vital driving function for strategic sourcing (Nair et al., 2015). Moreover, an increase in the number of suppliers and other stakeholders has rendered complexity; thus, procurement requires advanced technological capabilities to manage and leverage competitive advantage in supplier selections (Barrad et al., 2020) to ensure optimised sourcing. BDA could be a strategic lever in ensuring public procurement optimisation. In the future, big data-enabled procurement analytics will not just understand current spending. Instead, it will provide optimal solution-oriented insights to know end-to-end supplier performance, associated risks, and opportunities in procurement by generating visual maps based on procurement results (Handfield et al., 2019). One of the salient features of optimisation of any supply chain is resource-sharing and optimal resource distribution among entities. Inter-organisational learning between an organisation and its partners in supply chain networks is crucial to achieving this optimal resource distribution. BDA can stimulate inter-organisational learning and analysis of procurement and delivery

patterns, which can lead to greater optimisation of asset distribution and use of assets (Chen et al., 2016).

The extent of data generated by business, public sector, scientific research, etc., includes textual content to multimedia such as audio and videos, and 90% of the data generated globally is unstructured (Sivarajah et al., 2017). The public procurement ecosystem is no exception to this reality. Standard statistical tools and information systems need to be more robust to deal with such heterogeneous and unstructured voluminous datasets (Choi, 2019; Choi et al., 2018). (Papadopoulos et al., 2017) utilised unstructured big data generated from social media to develop a framework to explain supply chain resilience and uncovered that information sharing is an essential enabler for supply chain resilience towards disasters. The public procurement ecosystem, which also generates great volumes of unstructured data, can be better optimised with the power of BDA. Recent research confirms that technologies such as BDA, Blockchain, and IoT can be a reliable tool for enhancing public procurement performance from different aspects, including optimisation (Altundag & Wynn, 2024; Andrade et al., 2024; Chytilová et al., 2024; Govindan et al., 2024; Hm et al., 2024; Jantaro & Badir, 2024; Rai et al., 2024; J. Zhang et al., 2022a).

The government has a fiduciary responsibility to allocate scarce public resources across different competing priorities; therefore, anticipating the chance of occurrence of a given outcome is crucial. Early detection of fraud, malfeasance, or inefficiency is a key area where predictive tools can facilitate the optimised use of public goods (Gallego et al., 2021). BD can also be leveraged to develop green products and, thus, develop a sustainable supply chain through cost optimisation, a consequence with a positive impact on all three pillars of sustainability (Joseph Jerome et al., 2021). Besides relevance to sustainability-related outcomes, supply chain resilience has attracted significant attention due to increased uncertainty regarding rapid urbanisation and climate change.

Studies that are reviewed in this literature survey confirm that BDA positively influences all procurement phases, and firms utilising unstructured data, besides structured procurement data, could yield more benefits than their counterpart (Moretto et al., 2017). Data-driven analysis is empirically proven to secure optimal purchasing decisions in large-scale procurement (J. Zhang et al., 2022b). The power of BDA is also empirically utilised in indexing malafide intention, where any public organisation needs to secure optimal procurement with a specific reason

(Fazekas et al., 2016). Therefore, the role of BDA in procurement optimisation is empirically tested in various settings, and further studies into the healthcare supply chain of a developing country can validate the existing findings.

### 2.7.4 Digital procurement practices in public procurement

Embracing innovations in public procurement is no longer a breaking news, as the link between innovation and public procurement is now well-documented (Mwesiumo et al., 2021). Particularly in the new era of Industry 4.0, in similitude to every other business function, procurement also utilises the power of cutting-edge, state-of-the-art disruptive technologies. The key focus of Industry 4.0 is to automate the current manual procurement process using digital technologies, thus reducing uncertainties through increased transparency in exchanging information among the supply chain partners (Altundag & Wynn, 2024; Bag, Wood, Mangla, & Luthra, 2020; Govindan et al., 2024; Sjödin et al., 2023).

The introduction of innovation in public procurement practices essentially constitutes an organisation-wide change; particularly, it is highly likely to disrupt organisations' routines and habitual practices (Mwesiumo et al., 2021). While buyers and procurement professionals assess and manage associated risks in their supply chain, digital technologies and data analysis are key factors in managing procurement activities effectively (Caniato et al., 2020). Thus, firms have started to gradually adopt digital procurement practices across their organisations. Digital procurement practices use advanced digital technologies, such as BDA, for procurement purposes and are committed to fundamentally changing the way a firm collaborates with its supply network worldwide (Kosmol et al., 2019).

Firms that adopt digital procurement practices can be classified based on the type of technology they use. For example, (Srai & Lorentz, 2019) distinguish between basic and advanced digital technologies for procurement. Once much-hyped e-procurement, the sourcing of goods and services by electronic means, falls under basic digital technology in the advent of disruptive technologies (Ramkumar et al., 2019). However, as new technologies emerge, the mere adoption of e-procurement is insufficient to keep pace with the suppliers and other procurement stakeholders proficiently using advanced digital technologies. Advanced digital procurement technologies include more recently emerged technologies such as IoT and BDA (Srai & Lorentz, 2019).

Being the central interface between the internal and external business partners, procurement is a unique business process that consumes 'big data' that flows between suppliers and procuring entities (Handfield et al., 2019). Supply chain practitioners expect procurement to tap these data's potential through predictive BDA tools such as pay-per-use contracting models or artificial intelligence (AI) enabled price and supply forecasting (Kosmol et al., 2019). In the case of public procurement, advanced digital technologies also have great potential to solve many long-standing challenges. For example, blockchain can potentially solve the perennial transparency problem in public procurement by utilising its shared storage, allowing many people to share the same information (Weingärtner et al., 2021). Public procurement authorities can incorporate blockchain technology into their digital procurement portfolio.

Innovation in public procurement has recently emerged as a vital policy instrument, and public procurers have recently turned their eyes to innovation contests to support public procurement innovation (Pihlajamaa & Merisalo, 2021). Consequently, public sectors across the globe embrace innovation in their procurement practice more rapidly than ever before. Therefore, the latest technologies are now empirically proven to help curb public procurement irregularities. For example, by using a novel 'Big Data' approach, a composite indicator of high-level institutionalised procurement corruption was developed to measure grand corruption in public procurement and thus minimise allocating public procurement contracts by bending prior explicit rules to benefit a particular closed network by denying equal access right to all others (Fazekas et al., 2016).

Apart from a positive effect in the reduction of corruption and an enhancement in market price awareness, historical price analysis is also critical in winning best-value public procurement. A recent study shows that procurement cost parameters and unit transportation cost values are both critical in reducing operational costs in government large-scale food grain procurements (Mahapatra & Mahanty, 2021). Data-driven technologies such as BDA can help governments make the most informed decisions by providing current market price trends, historical price changes, and market response to the global situation in the past and future projections (Kaur & Singh, 2018; J. Zhang et al., 2022b).

According to the World Economic Forum, the single largest challenge that stifles economic, social and environmental development is public-sector corruption, which centres around a lack of transparency (Weingärtner et al., 2021). A study shows that a procurer can manipulate the

expected size of a public contract to drive the value of that contract below the threshold to award a contract to a particular business (Plaček, Nemec, Ochrana, Schmidt, & Půček, 2019). Lack of transparency in public procurement contributed significantly to the overall public sector irregularities, and automation of the full procurement cycle was considered a panacea to eliminate this problem (Moretto et al., 2017). However, with the advent of new technologies, mere procurement process automation will not suffice to keep pace with the large volume of data that is generated through business processes (Dávid-Barrett & Fazekas, 2020). Therefore, the incorporation of the latest technology into the procurement process is overdue in the public sector if it is not already done (Carvalho, 2019; Mavidis & Folinas, 2022; Mavidis et al., 2024; Siciliani et al., 2023). The latest technologies are empirically proven to analyse procurement irregularities, such as the indexation of corruption in public procurement (Fazekas et al., 2016). Therefore, government organisations should aim to adopt cutting-edge digital technologies into their procurement business process to maximise the return from public funds. Organisational digital procurement practices, therefore, need to be updated accordingly.

## 2.8 Literature Review on Sustainability Performance of Healthcare Supply Chain

### 2.8.1 Healthcare supply chain

A supply chain is a process or journey that starts with the input of unprocessed raw materials and ends with final finished goods for customer use, in which many stakeholders, including vendors, service providers, and customers, are interlinked in the supply chain process (Vitasek, 2013). Therefore, a supply chain could be seen as a system or process with at least two entities but usually more than two, such as suppliers, manufacturers, carriers, retailers, and consumers.

Unlike the supply chain of traditional products based on supply and demand, healthcare cannot be stocked as part of its supply chain (Ageron et al., 2018; Benzidia et al., 2023). Therefore, the healthcare supply chain is entirely different from traditional business supply chain processes (Benzidia et al., 2023; Daú et al., 2019; Getele et al., 2020; Kargar et al., 2020). Continuously changing patterns of care needs and patients' expectations, added to the highly regulated nature of the sector, pose unique challenges. A survey conducted by Black Book in 2016 found that 69% of IT leaders consider the healthcare supply chain as the most critical part of actionable data mining, even more than the EHR in use (LaPointe, 2022; Petrick & Gadaleta, 2020). Another study on hospital staff surveys found that 78% of the respondents manually processed inventory at any point in the supply chain. Only 17% of the healthcare facilities had implemented an automated supply chain process to track their product and inventory in real-

time (Kerr, 2017). It is unlikely that those healthcare firms, without an inventory tracking system, would implement other high-end supply chain technology like Radio Frequency Identification (RFID) technology and computerised provider order entry (CPOE) system, the same study opined.

On the other hand, with the emergence of sophisticated treatment processes, coupled with an increase in the number of aging patients, the overall healthcare cost has been rising. The consumer always wants to get high quality at a low price. Patients are no exception. Moreover, in healthcare, it comes as a fundamental right of a human being (dos Reis; Jain, 2023; Mahdanian et al., 2023; Maryanto & Rohmansyah, 2024). Surprisingly, where slashing costs of healthcare services remains a global concern, the irony is that a 2017 report by the OECD found the lion's share of total healthcare spending among OECD countries is ineffective and even wasteful in some cases (OECD, 2017). Therefore, in the context of wasteful healthcare spending, this waste could be synthesised from various dimensions, such as:

1. The process and services do not deliver benefits for the stakeholders.
2. Cost management was not optimal in the value chain. Particularly, costs that could be avoided with innovative alternatives have not taken place.
3. High administrative costs and inefficiency in the delivery of care

30-50% of overall US health spending is considered wasteful, which is as high as 1.9 trillion US dollars per year (Olivares-Tirado & Zanga, 2024). Unlike other supply chains, the healthcare supply chain entails additional regulatory and administrative costs. Research confirms that administrative complexity is the most outstanding contributor to wasteful spending in the US healthcare system (Olivares-Tirado & Zanga, 2024). The OECD report recommendations for reducing wasteful spending include a better way to use information through a robust intelligent system in the supply chain, an organisational change and better coordination among healthcare providers for better procurement and sourcing of healthcare products and services. A significant share (>30% of total healthcare spending) of healthcare spending remains in logistics. For example, hospitals represent almost 29% of total healthcare, of which more than 30% is linked to logistics (Volland et al., 2017). Hence, the implementation of best practices can reduce half of the logistics costs of healthcare (Pimentel & Mora-Monge, 2024; Poulin, 2003; Sampieri-Teissier et al., 2024).

Surprisingly, there are no standard best practices in healthcare supply chain management. Harvard Business School referred it to represent a paradox in healthcare supply chain management, as it being a home of some of the best and the worst practices (Byrnes, 2004). The opportunity cost of inefficiency in the healthcare supply chain is enormous and affects every citizen, as almost twenty-five per cent of hospital costs are supply-related (Gerami et al., 2020; Kessy et al., 2023; Longaray et al., 2023). Supply chain inefficiencies eat up limited resources that could be utilised to make vital medication more affordable and widely available.

The European Court of Justice declared healthcare as a service (Sunol et al., 2009). However, healthcare is not merely a thing or service to be given, sold, or purchased; instead, healthcare is an entire ecosystem related to an individual's or community's well-being, of many connected moving parts (Bevere & Faccilongo, 2024; Goodair & Reeves, 2024; Ungaro et al., 2024). These parts are connected through the existence of patients. The healthcare ecosystem is the summation of many important interconnected branches, including the pharmaceutical industry*, the* Biotechnology industry, *the* Healthcare equipment industry, *the* Healthcare distribution industry, Healthcare facilities, managed healthcare, etc. (Belciug & Gorunescu, 2020; Sadeghi & Mahmoudi, 2024).

The healthcare industry needs to improve its visibility by making smart decisions through the integration of the entire supply chain leaving traditional operations in silos. On the other hand, traditional health information technology currently in place limits progress, considering the continually growing trend of individualised and patient-centric care (Yaeger et al., 2019). Traditional health technology assessment (HTA) is also developed to guide policymakers in making regulatory and funding decisions through a data modelling and evidence synthesis framework, aiming at clinical excellence, cost efficiency, safety, and budget impact on treatments (Doctor & MacEwan, 2017). Therefore, traditional Health IT (HIT), for example, contemporary EMR, serve more than institutions rather than patients, even though traditional HIT attracts high administrative costs and lacks universal data access.

Hence, healthcare researchers are now advocating for the incorporation of the latest technologies, i.e., blockchain. IoT, BDA, etc., to make health data interoperable and robust, eventually making the healthcare supply chain more efficient and intelligent. Even though necessary technological resources are available, effective incorporation of those into practices is difficult due to the complex nature of the healthcare context (Chioma Anthonia et al., 2024; Malathi et al., 2022; Nelly Tochi, 2024). An interview conducted among healthcare supply

chain experts by (McKone-Sweet et al., 2005) revealed that the lack of effective use of available data was of more concern than the lack of information systems in the healthcare supply chain.

BDA can effectively handle this gap and become a critical support for supply chain management (Chen et al., 2020). On the other hand, one of the crucial components of the current healthcare information technology is the efficacy in the collection of data and the ability to integrate the required data to create an information flow in the whole supply chain (Solovy, 2004). The latest studies, such as (Lintern & Motavalli, 2018), also support the struggle for existing information technology system maturity in the healthcare supply chain. Therefore, having proper BDA capabilities for integration of a holistic and robust technology like BDA is also essential, in addition to just deciding on BDA implementation in any healthcare supply chain.

### 2.8.2 Green procurement and sustainable supply chain

Since the declaration of the Sustainable Development Goal (SDG) agenda of the United Nations, responsible sourcing has received increased attention worldwide. Hence, attention was paid in this research to pulling what was discussed specifically on green procurement from a sustainability standpoint. This study confirms that, in responding to the global call for protecting the environment, governments across the globe increased their awareness of the importance of considering the impact of public purchase activities (Bader Khamis AlNuaimi et al., 2021).

A new practice termed as ‘Green Procurement’, or GP, emerged at this vantage point. The European Union (EU) first proposed GP standards and related environmental protection regulations (Fu et al., 2019). GP capabilities enable a firm to achieve a competitive advantage over its competitors (Liu et al., 2020). GP can exert either directly or indirectly a positive impact on an organisation's overall environmental performance (Liu et al., 2020). GP is particularly important for public organisations due to its greater impact and reach on all other formal and informal sectors of the country's economy (Bader K. AlNuaimi et al., 2021). However, the implementation of green procurement in a firm is an extremely challenging task, even though no one denies the importance of GP in achieving higher environmental performance (Bader Khamis AlNuaimi et al., 2021). It is even more challenging to implement in the public sector than in the private sector (Grandia & Voncken, 2019). This complexity is

due to the wide range of environmental criteria for different groups of products and public services that firms regularly procure.

In 1987, the United Nations coined the term sustainable development, which meant meeting the present's needs without compromising the ability of future generations to meet their needs. That was the start of the new phrase, sustainable as an adjective, and posed a new conceptual evolution process in motion (Appleton, 2006). During the past several decades, the word 'sustainability' and the implementation of its core principle into operations have been on the discussion agenda in scientific and political forums across the globe. The holistic target attached to the definition of sustainability creates many complexities when applied in practice (Peano et al., 2015). After the Sustainable Development Goal 2030 was disclosed by the United Nations, the concept of sustainable or sustainability, soft around the edges, has now had an enormous, global resonance (Giordino et al., 2024). The concept of sustainability stands on three pillars: economic, environmental, and social- also informally resembles profits, planet, and people. The "social" component has recently been integrated into sustainability debates (Eizenberg & Jabareen, 2017). In a broader sense, we can conclude that sustainability encourages enterprises to consider years and decades, rather than just the next quarter's income statement, in framing decisions and consider factors beyond profit or loss. In particular, sustainability feels an obligation to the environment and society. There is a tendency to interchangeably use sustainability with the green concept. However, all three pillars of sustainability are integral to making a business or process sustainable. Most of the existing empirical studies on sustainable supply chains deal with economic and environmental dimensions, confining their studies to the trade-off between environmental consequence and cost management, leaving out social performance consideration (Das, 2018). Fewer studies (Lu et al., 2012; V. Mani et al., 2016; Venkatesh Mani et al., 2016; Zhu et al., 2016) considered only the social dimensions of sustainability in the supply chain, entirely ignoring the other two aspects. However, it is widely accepted that the concept of sustainability is the integration of any supply chain's economic, environmental and social impact.

A Sustainable Supply Chain (SSC) integrates environmentally friendly practices, social responsibility, and economic efficiency throughout the supply chain process. It focuses on reducing environmental impact, promoting ethical labor practices, ensuring product safety, and contributing to the well-being of communities while maintaining business profitability and competitiveness. Drumwright (Drumwright, 1994) first pointed out the sustainability issue in

the supply chain by suggesting that firms consider social responsibility instead of solely focusing on profit maximisation. Social responsibility is acting in the best interest of both the environment and society. With the incorporation of environmental and social agenda into the traditional supply chain management, sustainable supply chain management (SSCM) extends the realm of conventional thinking into the inclusion of sustainability of economy, environment, and society while designing and optimising the supply chain (Hong et al., 2018). Many researchers' efforts to define SSCM coincide with the definition as SSCM is SCM focusing on economic, environmental, and social stability for long-run sustainable growth (Dubey, Bryde, et al., 2020; Dubey et al., 2016; Dubey, Gunasekaran, & Childe, 2019).

Ahi and Searcy (Ahi & Searcy, 2013) identified twelve definitions for SSCM and twenty-two definitions of traditional SCM to distinguish green SCM from SSCM. They concluded that the latter is an extension of the former by extending the environmental dimensions of the supply chain into the economic and societal dimensions to make the former sustain long-term growth. Scholars have done numerous studies on supply chain efficiency. However, lesser efforts have been directed to SSCM-based practices (Hong et al., 2018). Some studies are carried out on how SSCM practices enhance firm performance. For example, (Hasan, 2013) researched five typical firms, such as Coca-Cola and Estman, and found the positive impacts of SSCM not only on environmental performance but also on firms' operational excellence. Wang et al. (Wang et al., 2013) found a positive correlation between firms' SSCM practices and financial performance. So, we can loosely conclude that SSCM is not just thinking green; it is a holistic approach to attaining long-term overall operational excellence for a firm. The more innovations are integrated into this approach, the more success a firm can harvest. Recent research also espouses this claim. For instance, a leading paper manufacturing company in Java, Indonesia, customised its supply chain process by applying a combination of different innovative models, including the sustainability-oriented innovation (SOI) model. The procedure successfully brought a tangible return for the company, such as a reduction of 25 % in inventory and a 3% increase in sales (Paul & Zhou, 2017). However, no similar study could have been located in the healthcare supply chain, let alone emphasise the procurement function of the entire supply chain.

### 2.8.3 Impact of BDA on the 'sustainability performance' of the supply chain

Any supply chain activity has a consequence on the environment, global warming, and climate change. It even costs human lives due to the emission of greenhouse gases, improper waste,

hazardous and explosive substances management, and production of non-biodegradable products (Agyabeng-Mensah et al., 2020; Feng & Sheng, 2023). As a result, during the past several decades, the concept of sustainability has increasingly captured public attention and has been firmly positioned at the centre of international policy (Merino-Saum et al., 2020). Apart from the manufacturing industry, the concept of sustainability has continued to showcase significant value in other sectors, such as construction and project management (Stanitsas et al., 2021). Firms from various sectors are adopting green and social approaches into their supply chain to rein the negative impact of their activities on the environment and society to gain a competitive advantage and meet stakeholders' requirements in accessing new markets (Agyabeng-Mensah et al., 2020).

As a logical consequence, the measurement of the 'sustainability performance' of firms becomes a niche area for research. Various sustainability performance measurement indicators, indices, and scales have recently been theorised. However, there is a genuine lack of theoretically justified and empirically validated integrative performance measurement scales for the sustainable supply chain (Chowdhury et al., 2020).

Recent studies confirm that BDA positively impacts a firm's internal process and sustainability performance (Ali et al., 2020; Aziz et al., 2024; Mesquita et al., 2023; Raut, Mangla, et al., 2021; Singh & Joshi, 2024; D. Zhang et al., 2022). However, apart from mere technology, management and leadership style, policies, supplier and customer integration, and internal business process integration significantly influence supply chain sustainability practice (Raut et al., 2019). Hence, the building of BDA capability is of paramount importance to making BDA useful toward sustainability. For the digital transformation of the supply chain through the use of disruptive technology such as BDA, IoT, Blockchain, etc., having the appropriate skill set and capabilities is crucial to successfully integrating technology.

Existing research on sustainability-related issues of digital transformation usually concentrates on the implications of how digital transformation provides opportunities for ecological efficiency improvements through better resource efficiency (Beier et al., 2017). However, digital transformation in logistics and supply chain management has yet to reach maturity; hence, the impact of sustainability has ample room to improve and change. The sustainability impact of digitisation of the logistics and supply chain, with regard to economic dimensions, is more important than that of environmental and social dimensions (Kayikci, 2018). Future

research is required to elaborate on new opportunities created by digital transformation, including the sustainability impact (Beier et al., 2017). On the other hand, the existing body of BDA in sustainable supply chain knowledge covers different areas, including manufacturing, banking, oil, and gas. However, BDA to achieve a sustainable supply chain in the service sector, like healthcare, is rarely discussed separately. The summary table relating to recent BDAC research, which is appended in Appendix A, would support this claim.

A study (Junge, 2019) provided an overview of conceptualisations, a proposed framework for the digital transformation of logistics, and sustainable supply chain management. The change to a sequentially interconnected sustainable supply chain of many stakeholders will generate big data of diverse types and forms, which requires a solid, capable system to ensure their effective use (Chen et al., 2019). Therefore, traditional data processing tools are ineffective in processing big medical data (Awrahman et al., 2022; Sadiku et al., 2020), including procurement metadata (structured and unstructured). Keeping pace with the growing interest in BD has led organisations to integrate BDA into their supply chain (Fosso Wamba et al., 2018) to obtain valuable information that facilitates a competitive advantage in business by nearly accurately predicting an uncertain future (Lamba & Singh, 2018).

As mentioned in the previous sections, the existing studies demonstrated the role of digital technology as a whole, not focusing on any particular disrupting technology such as BDA. Among the filtered articles in this literature review, a limited number of studies are available that confirm the use of BDA outputs for the decision-making process of sustainable context and the role of BDA in sustainability through procurement optimisation. On top of that, there are minimal studies found in the healthcare sector, let alone the sustainability performance of the supply chain in healthcare [Appendix A of this thesis]. So, studying the role of BDAC on healthcare supply chain sustainability and seeing through the mediating lens of procurement optimisation is overdue.

Despite an increased level of attention to the sustainability of supply chain management, existing literature has failed to address the dimensions of sustainability (Song et al., 2017). However, new technologies such as IoT are becoming key drivers of supply chain sustainability (Kamble et al., 2018). The massive data IoT generates from interconnected supply chain entities could be analysed efficiently through BDA to achieve sustainability in three dimensions (Verdouw et al., 2016). BDA contributes to the strategic objectives of the organisations, and

strategic planning supports the supply chain sustainability performance (Mesquita et al., 2023). Strategic capabilities define the sustainable existence of business entities (Hofmann & Rutschmann, 2018). Considering the high level of environmental uncertainty, organisations must adopt approaches and processes using BDA to achieve sustainable supply chain performance (Mesquita et al., 2023; Singh & Joshi, 2024). Supply chain performance depends on the implementation of innovation to support performance. A study by Wamba et al. (Wamba et al., 2017) on the ways firms could leverage BDA provided evidence of enhancing organisational capability by using BDA to improve sustainability performance.

### 2.9 The Missing Link: BDA in Public Procurement in Healthcare

As it is discussed above, BDA has brought enormous benefits to many sectors. Recent research reported a direct positive impact of BDA on a firm's performance. However, the impacts of BDA on public procurement are rarely discussed, particularly in the healthcare public procurement area, which is identified as a gap in the existing BDA research. Although a few articles are available and listed in Appendix A's summary of the article table, they are not directly related to the impact of BDA on public healthcare procurement. Addressing this gap is essential. Particularly when the whole world is now stressed with healthcare spending due to COVID-19. Developing economies were hit hard by this pandemic. Hence, they have no other way but to search for ways to optimise their healthcare procurement through technology.

After my initial finding from the literature survey of the gap in studies addressing the impact of BDAC on healthcare public procurement, I, then, aimed to find a candidate context for this study. I, broadly, had two options to consider: either to investigate this gap in the context of a developed economy or that of a developing economy.

As it is reported in Appendix A's summary of existing BDAC articles, approximately 40 of the 104 shortlisted current BDAC studies screened were carried out in developing economies. This disparity will be more prominent if the excluded articles for this literature review are also counted. Even with the count of 40 studies in a developing country context, there is a catch. Many countries reported as developing, as per the existing definition, are indeed high-income countries and are in transition from high-income developing countries to developed countries. For example, Malaysia, UAE, etc. So, the number of studies conducted in low-income developing countries is below 15%, meaning most of the existing BDAC literature covers either developed or high-income developing countries.

Therefore, I considered a country that resembles most the nature of a low-income developing nation. Bangladesh is such an example. Therefore, Bangladesh has been chosen to serve as the

context of this investigation, where the present scenarios of public procurement in this country are discussed in the following section.

### 2.9.1 Key issues in public procurement: the Bangladesh's health sector perspective

In this section, a brief description of key issues in current healthcare procurement in Bangladesh has been discussed to justify the reason for selecting Bangladesh as a case study.

Over the last decade, public procurement expenditure in OECD countries increased significantly to 11.8% of GDP in 2007 and jumped to 12.9% in 2021 (OECD, 2023). Among low- and middle-income countries, the public procurement figures are approximately 20-70% of national income (Adjei-Bamfo et al., 2019). In 2018, the total global public procurement amounted to $11 trillion, nearly twelve per cent of the global GDP of around $90 trillion (Getaneh & Yeshanew, 2020). The latest research also indicates that one-third of global government spending goes to public procurement, which is more than 10 trillion annually (Fazekas et al., 2024).

In Bangladesh, which represents this research context, procurement is also a significant government activity, impacting public services such as health, education, water, and infrastructure. Total spending on public procurement is about $16 billion, one-third of its annual budget. $13 billion out of this spending is spent on the procurement of goods, works, and services in implementing development programs, constituting approximately seventy per cent of the country's aggregate development outlay in the annual budget (Islam, 2018).

It is reported in the literature that most governments of developing countries often fail to maintain due diligence in the public procurement process, leading to inefficiencies, irregularities and harsh environmental and socioeconomic consequences (Adjei-Bamfo et al., 2019). Bangladesh is no exception. The literature review revealed that procurement reform was identified as one of the top priorities to improve overall public sector governance (Ahsan & Kumar Paul, 2018). Accordingly, to overhaul the country's public procurement process, the World Bank provided funds for the Public Procurement Reform Project- 2002, which was implemented between 2002-2005 and extended to phase two until 2020 (Bank, 2016). Electronic government procurement (e-GP) is making remarkable headway in automating the procurement process in Bangladesh. However, e-GP is mainly an outcome of procurement 3.0, which manages the complete purchasing cycle and usually does not integrate data across the

whole supply chain network. For instance, in the public sector, e-GP is end-to-end automation from sourcing (pre-award-before supplier selection) to purchase (post-award-after the supplier selection) phase (Adjei-Bamfo et al., 2019). As a result, e-GP needs to catch up with voluminous data; the public procurement process is increasingly generating every day.

In contrast, procurement 4.0, the latest development in the sector, involves digital transformation through integrating data across the whole supply chain network (Bag, Wood, Mangla, & Luthra, 2020). A recently introduced e-GP system replaced the existing manual bidding document management. However, no evidence or support from the literature is found in favour of removing many gross procurement inefficiencies, as explained in the next section. So, it is evident that Bangladesh needs to integrate disruptive technologies such as blockchain and BDA in its public procurement framework to get the true benefits of digital transformation in handling big unstructured data sets generated from the country's procurement ecosystem. It could help to overcome the limitation of e-GP to optimise the whole supply chain network, managing gigantic structured and unstructured data. Such an initiative will escalate Bangladesh's procurement reform to the procurement 4.0 stage and facilitate the removal of prolonged, unresolved inefficiencies of public procurement.

In particular, if we investigate the healthcare sector, we see that spending on healthcare in Bangladesh is not at par with that of high-income countries around the world. The proposed budget allocation for the health sector of the country was only 5.2% of total budget expenditure in the year 2017-18, whereas WHO recommends at least 15% budget allocation in the health sector of countries like Bangladesh (Fahim et al., 2019). In the latest budget [2024-2025], the budget allocation for healthcare is approximately 5.2% of the total budget and a mere 0.74% of the GDP (Khatun et al., 2024).

Such a poor allocation imperatively affects the spending in the health procurement sector, which, in turn, contributes to making the overall supply chain inefficient. While the lack of sufficient funds for required supplies is a factor behind such inefficiency, the lack of an appropriate and consistent database and available resource optimisation mechanism to accurately predict the demand for the supplies and logistics requirements in particular facilities also plays a significant role. Moreover, due to the lack of both system data and academic studies, the extent of this problem is hard to estimate. However, a considerable amount of unstructured data, such as media coverage, reports, etc., regularly portrays the existing

healthcare problem. Several factors play a part in making the overall health sector procurement ineffective, particularly not optimised. The following paragraphs explain four key factors: the lack of a data-driven procurement engine, lack of just-in-time delivery of products and services, lack of predictive analysis, and lack of suppliers' appraisal mechanism.

1) Lack of data-driven procurement engine

To begin with, Bangladesh doesn't have any efficient technological means in the procurement sector at present. The only existing program, called eGP, which was introduced by the then Central Procurement and Technical Unit of Bangladesh in 2016, is a fundamental tender processing tool for comparing bidding prices on specific criteria (Group, 2023). The actual need assessment of the procurement, validation of procurement requisitions, and predictive need assessment, as well as early prediction of different irregularities, are absent in the existing e-GP system.

As a consequence, procurement optimisation could not be achieved, and the whole supply chain supper, including healthcare. In healthcare, the unavailability of medical supplies, including drugs, is almost a perpetual problem in nearly every public hospital throughout the country. The lack of an efficient healthcare supply chain, timely procurement and timely release of the funds to pay for supplies make the situation worse. A lack of procurement optimisation as a result of improper purchase and maintenance planning using a manual or standalone system further fuelled this inefficiency. It is reported that almost 65% of the ambulance services are non-functioning at any point in time, either for lack of maintenance budget or not timely allocating other resources, such as drivers or funds for fuel (Islam, 2014). Furthermore, basic medical equipment such as an X-ray machine or general pathological testing services remains non-functional a lot of the time owing to the need for repair or replacement or the absence of skilled professionals to operate.

2) Lack of Just in Time (JIT) delivery of products and services

Secondly, health governance has an interdependent multimodal system in place. The health sector probably has the highest number of interlinked organisations in the organogram, both vertically and horizontally, with complex and overlapped responsibilities, which significantly contributed to the inefficiency of healthcare procurement and eventually contributed to making the whole supply chain ineffective. Because of weak coordination among organisations in different layers, a byproduct of not having a data-driven supply chain, the resources are allocated at different times, resulting in the procurement being incomplete and valuable

resources being wasted in the meantime. For instance, when gynaecologists and other relevant support staff are assigned, the surgical equipment procurement will be delayed, leaving already designated health professionals unused. Even after a significant delay, if the necessary equipment arrives, many incidents can occur where that equipment cannot be operated due to a lack of required training or other technical requirements.

3) Lack of predictive need assessment and optimum resource allocation

Thirdly, many such incidents are available where all costly medical equipment procured is kept unopened for years due to a lack of technicians to run cutting-edge technology. The central procuring authority neither has a particular method for any health purchase requisition nor a predictive model to accurately identify future needs. Hence, costly resource waste becomes inevitable due to insufficient timely handshaking of different components to optimise the procurement. Notably, the technology purchase cases in the health sector of Bangladesh are rife with tantamount instances of failure or utter mismanagement to the degree of technology obsolescence even before the installation or operations begin, resulting in the enormous waste of taxpayers' money and inefficiency in the health sector. Some recent reports from national dailies make this claim evident.

A recent media report highlights that essential medical equipment in District Khulna's government hospitals remains unused or out of order, compelling patients to seek expensive services at private clinics. Notably, equipment such as MRI and CT machines and a BDT 800 million linear accelerator for cancer treatment have languished for years without repair. This negligence has led to a surge of unauthorised private facilities, where patients often receive substandard care. Transparency International Bangladesh attributes the situation to the health ministry's failure and alleged corruption, as officials reportedly refer patients to private centres for personal commissions. Efforts to improve the situation remain inadequate (Sheikh, 2023). Another recent media report reveals that many X-ray machines procured earlier remain unused for 28 years because of not sourcing proper manpower to operate them (Deshwara, 2023).

There are reports highlighting critical inefficiencies at Bangladesh Medical University’s (erstwhile Bangabandhu Sheikh Mujib Medical University -BSMMU) super-specialised hospital, inaugurated in September 2022. Designed to treat 5,000 patients daily, the hospital currently serves fewer than 500 due to significant shortages of doctors, technicians, and support staff, compounded by corruption in recruitment practices. Alarmingly, 90% of the $33 million

medical equipment purchased from South Korea remains unused, with some warranties nearing expiration, resulting in additional maintenance costs. This facility, funded by a Tk 1,047 crore loan, was intended to provide low-cost, high-quality healthcare but is instead becoming a financial burden on the public. Patients face long wait times for consultations and pay fees comparable to private hospitals (Anam, 2024). This situation reflects a broader pattern of mismanagement in the public health sector. Urgent action is needed to address systemic issues in procurement and staffing to ensure the hospital fulfils its intended purpose and serves the community effectively.

In a more shocking report, which appeared in the daily “Prothom Alo”, the country's leading newspaper, more than 233 small to medium-sized hospital facilities remain unused. A recent report reveals the stark failure of healthcare facilities in Bangladesh, highlighting the abandonment of several 20-bed hospitals across the country. Many of these facilities, inaugurated over a decade ago, remain non-operational, overrun with weeds and debris, while others have never admitted patients. Significant investments, such as approximately Tk 800 million for some establishments, have been wasted due to a lack of a necessary workforce and equipment. The health ministry identified 233 unused facilities, many constructed without proper planning or consideration of staffing needs. Officials acknowledge systemic issues in health project management, where facilities are built based on individual interests rather than community needs. This mismanagement resulted in a substantial waste of resources, leaving many rural areas without essential healthcare services. Bangladesh Medical Association expressed deep concern over this ongoing issue, urging the government to address staffing and operational deficiencies to effectively utilise these facilities (Moral, 2022).

4) Lack of dynamic performance appraisal of suppliers

Fourthly, currently, there is no performance measurement system for suppliers. There is an allegation that there is a nexus of dishonest health professionals and unscrupulous suppliers who bag unethical deals. Overpricing is a common phenomenon in Bangladesh's public procurement, resulting from the inefficiency of the existing standalone system in extracting more usable information from structured and unstructured data. A recent study finds that health-sector corruption during the COVID-19 pandemic was pervasive across all stages, including procurement, testing, and treatment in Bangladesh. Through an analysis of 2,588 articles from leading newspapers, researchers identified 97 articles specifically addressing corruption issues. Key findings reveal that frontline health workers were provided with low-quality masks,

compromising their safety. Additionally, some private facilities issued fake COVID-19 certificates and sold overpriced medicines and equipment, with one hospital reportedly providing nearly 2,000 test certificates without any testing. Personal protective equipment (PPE) cost was often inflated, and different government hospitals purchased Meropenem injections at unusually high prices. While measures were taken to combat corruption, such as filing cases and issuing arrest warrants, some accused individuals were released on bail. Despite facing challenges from government denial and indifference, the media played a crucial role in exposing these corrupt practices, ultimately highlighting the severe lack of transparency and accountability in the health sector (Khanam et al., 2023).

A similar situation is also reported in many other developing countries; for example, medical equipment worth billions of dollars remain idle in many regional hospitals in Uganda (Nabakooza, 2024). As discussed in the earlier section, ABDM can facilitate understanding the supplier better and leveraging the power of BDA can help mitigate this problem.

### 2.10 The Identification of Literature Gap and the Objectives of This Research

The motivation behind this study is fourfold. Firstly, despite past studies that have paid more interest in BDAC, primarily in the retail and manufacturing sectors, few studies have shed light on the service sector. Some studies are available in the research outlets, covering the service sector, which mainly focuses on digital transformation in general, not specific technology such as BDA integration. For example, a survey of how the combination of digital manufacturing, logistics, and equipment affects the service supply chain of complex products found direct benefits of introducing digital transformation in the supply chain of complex product manufacturing (Partanen & Holmström, 2014). Products related to healthcare are also highly regulated and complex, which requires a high level of precision. Another study, on a less-discussed issue like Forest-Based Supply Chain (FbSC), found that seamless integration of state-of-the-art digital technologies in forest supply actors, i.e., real-time data collection on forests, product flows, forest owners, harvest companies, haulage companies, etc., brings higher sustainability and efficiency of FbSC (Scholz et al., 2018). Hence, it is implied that digital transformation of the healthcare supply chain, a complex one, can pave the way to offer cost-effective healthcare solutions by delivering the right product to the right person at the right time using technological advancements, data analytics, connectivity among suppliers, and regulatory compliance. Both studies demonstrated the role of digital technology as a whole, not focusing on any particular disruptive technology such as BDA. On top of that, minimal studies are found in the healthcare sector, let alone the sustainability performance of the supply

chain in healthcare. Therefore, studying the role of BDAC on healthcare supply chain sustainability could bridge this gap.

Secondly, limited literature is available confirming the relations of having appropriate BDAC and the decision process of sustainable context, and the role of BDAC in sustainability. Some empirical studies are available indicating the influence of BDAC impact on economic, social, and environmental dimensions of sustainability; however, those are still fragmented (Song et al., 2017). Although some sectoral studies claim to improve three aspects of sustainability through better decision-making using BDA, the number of studies in the healthcare context is limited. The proposed research could contribute to filling the current gap.

Thirdly, the existing research espouses future BDA capabilities in reducing uncertainties in the supply chain through accurate predictions (Chong et al., 2016; Sagaert et al., 2018). However, there are significant organisational capacity differences between developed and resource-constrained countries. Even in developed economies, many organisations have a limited understanding of BDA capabilities (Arunachalam et al., 2018). Therefore, whereas successful BDA integration in the supply chain requires organisations to enhance their own BDA capabilities first, it also requires organisation-wide support to shift the power to acquiring BDA capability (Akhtar et al., 2018). Hence, a separate study on a low-resource country context is required for a more accurate outcome of the role of BDAC in the sustainable healthcare supply chain in a developing country context.

Fourthly, the traditional supply chain, including the healthcare supply chain, is linear with random movement through designing, planning, sourcing, making, and delivering (Machiani et al., 2024; Ransikarbum et al., 2024; Ravindran et al., 2023). Nowadays, the supply chain in healthcare is gradually transforming from static to dynamic, interconnected systems covering all partners in the ecosystem, including healthcare providers, patients, pharmaceuticals, life science firms, regulators, and others, and in a quest to make the system more robust and efficient (Nadeau, 2024). This shift from a linear to a sequential interconnected supply chain in the healthcare sector could be the building block to arrest the increasing healthcare cost and cover more populations deprived of quality healthcare worldwide (J et al., 2023; Sathiya et al., 2023). The successful implementation of this shift will affect how healthcare firms will compete in the future and respond to the crying need for low-cost healthcare services worldwide. BDAC could be a crucial measure to facilitate this shift positively.

To address the problem that has been described so far in light of the gaps that have been identified in the literature review, the following research questions have been aimed to explore in this research.

**R.Q.1.** How does BDAC enhance the 'sustainability performance' of the healthcare supply chain?

**R.Q.2.** Does procurement optimisation mediate the impact of BDAC on 'sustainability performance' of the healthcare supply chain?

> **R.Q.1.1.** How does BDAC facilitate the optimisation of public procurement in healthcare?
>
> **RQ 2.1.** How does the optimisation of public procurement affect the 'sustainability performance' of the healthcare supply chain?

This study aims to provide a managerial lever to improve healthcare supply chain sustainability performance. While BDA has brought many benefits to other sectors, it has not been articulately explained how technology such as BDA could help improve 'sustainability performance' in the healthcare supply chain in terms of complexity, volume, and cost optimisation. This study, in this light, aims to lay a building block in explaining these connections by making the following contributions. Firstly, it will explore Bangladesh's existing public healthcare supply chain, integrating emerging technologies in resource-constrained settings and procurement optimisation for achieving sustainability. Secondly, it will examine the organisation's capability to integrate BDA into Bangladesh's healthcare supply chain, where BDA has remained nascent. Without optimising the healthcare logistics sourcing, ensuring quality healthcare at an affordable cost is impossible. This study will contribute to providing a link between BDAC, the sustainability performance of the healthcare supply chain, and public procurement optimisation.

# 3. Research Framework

Chapter 2 discussed the concepts of Big Data Analytics Capabilities (BDAC), Procurement Optimisation (OPT) and Supply Chain Sustainability (SCS), which are the three core pillars of this thesis. The discussions that appeared in Chapter 2 attempted to provide a theoretical background that may facilitate the search for an answer to the three research questions that have been formulated and presented in the previous chapter. However, there is a need for the formation of a conceptual framework based on the literature that has been discussed. This chapter aims to develop a theoretical connection between variables, resulting in the formulation of the hypotheses of this research. Theoretical foundations from existing BDAC, OPT, and SCS literature are utilised to this effect. The existing literature's empirical findings are also utilised to facilitate the creation of this research framework. The following sections discuss the conceptualisation of the hypotheses of this research, which leads to the preparation of the final conceptual framework to be utilised in this research (this framework is presented at the end of this chapter).

## 3.1 Ground Rules of Hypothesis Development

Hypothesis development entails a specific, testable and predictive statement supported by theoretical positioning and/or prior empirical evidence (Bell et al., 2018; Cooper & Schindler, 2014; Kreuger & Neuman, 2006). Any good hypothesis must have at least three characteristics (Price et al., 2017).

1. It must be testable and falsifiable, which means the hypothesis must be testable using scientific methods, and there must be a possibility to gather evidence against the hypothesis if it is indeed false.
2. It must be logical, meaning previous theories/observations and logical reasoning should inform a hypothesis.
3. A hypothesis must be positive, meaning it should draw a positive statement of having a relationship or effect, not saying a relationship or impact does not exist.

I followed these basic rules in framing the hypotheses. The next few sections demonstrate how I developed various constructs to form a conceptual research framework.

## 3.2 BDAC and Healthcare Supply Chain Sustainability Performance

It is widely studied and empirically evidenced that BDA improves firms' economic performance (Ansari & Ghasemaghaei, 2023; Aziz et al., 2024; Aziz & Long, 2023; Aziz et al.,

2023; Chong et al., 2023; Faridoon et al., 2024; Syafrizal et al., 2023; Wittberg & Fazekas, 2023). However, as discussed in Chapter Two, a firm's performance is now seen through the sustainability mirror (Aziz et al., 2024; Del Sarto et al., 2024; Mesquita et al., 2023; Said et al., 2023; Singh & Joshi, 2024) to ensure that firms are not just focused on their economic performance, leaving all other societal and environmental well-being unaddressed. A few investigators studied the impact of BDA on sustainability performance. The literature review confirms that, even though still fragmented, some of the empirical studies indicate BDA's influence on three dimensions of sustainability (Song et al., 2017). Some existing literature also discussed the role of BDA in three separate dimensions of sustainability. Regarding the economic dimension of sustainability, BDA increases by 15-20% of Return on Investment (ROI) on supply chain activities (Ahmed et al., 2018). BDA can predict the financial impact of reducing losses and cost reduction (Roy & Roy, 2019) and, eventually, provide a strategic lever to grow revenue (Moro Visconti & Morea, 2019). BDA can help health settings maintain optimal inventory, which is crucial for optimal yield from healthcare spending (Samir et al., 2019).

Some recent studies found a positive effect of BDA in increasing environmental performance (Al-Khatib & Ramayah, 2023). Another study found a moderating impact of BDAC on environmental performance (Shahzad et al., 2022). The association between environmental concerns and BDA is relevant and essential to emerging markets such as India and Brazil (Song et al., 2020). BDA can efficiently monitor CO2 and greenhouse gas emissions (Jiao et al., 2018), helping conduct a more accurate environmental impact assessment necessary for optimum resource utilisation (Gupta et al., 2019). Hence, it facilitates decision-makers to understand better environmental impacts in the sustainable supply chain (Badiezadeh et al., 2018; Jiao et al., 2018). Environmental gains through integrating BDA can also bring economic gains through timely demand forecasts to reduce waste and inventory (Mani et al., 2017). In a time-driven service sector where every resource is required just in time, healthcare can also utilise the power of BDA to save energy and resources.

Social sustainability, the third component of the sustainability issue, also positively correlates with disruptive technology such as BDA. A study by (Badiezadeh et al., 2018) espoused a robust potential application of BDA in supply chains' social sustainability aspects. BDA inspires ethical practices among supply chain stakeholders and manages social concerns such as equality, discriminatory behaviour, forced labour, etc. (Mani et al., 2017). Big data can also

be leveraged to develop green products and, thus, develop a sustainable supply chain through cost optimisation, a consequence with a positive impact on all three pillars of sustainability (Joseph Jerome et al., 2021).

While it is clear from the above discussion that BDA positively impact the firm's performance in all three aspects of sustainability, organisational success in managing BDA projects' investment (Bakker et al., 2020; De Luca et al., 2020) and reliance on analytics-based insights in decision-making are crucial in gaining a competitive advantage over competitors (Akter, Gunasekaran, et al., 2020; Akter, Motamarri, et al., 2020; Faridoon et al., 2024; Khalil et al., 2023; León et al., 2024; Orero-Blat et al., 2024). Considering the different levels of BDA sophistication, an organisation needs to align its BDACs (Anfer & Wamba, 2019; Ferraris et al., 2019; Mikalef et al., 2019b; Rialti et al., 2019; Su et al., 2021b; Wamba et al., 2017), which is the core of our two hypotheses.

BDAC refers to the competence of a firm to provide business insights by capturing and analysing big data (Adiguzel et al., 2024; Aziz et al., 2024; Feng et al., 2024; Morimura & Sakagawa, 2023). In doing so, BDAC holistically utilises a firm's data, technology and talent as an organisation-wide process (Wamba et al., 2017). BDACs are the higher-order organisational capabilities in gathering strategic resources (Wamba et al., 2017). Researchers defined BDACs in various manners. BDACs are mainly categorised into two subcategories: human and non-human. A literature survey reveals several approaches to defining and assessing BDAC. It is conceptualised as a unidimensional construct (Dubey, Gunasekaran, & Childe, 2019) to comprise a multi-dimensional higher-order construct (Akter et al., 2016). A combination of mixed approaches is also found. For instance, (Lozada et al., 2019) used second-order human capability constructs to form two other second-layer constructs extended up to the third-order to eventually form the first-order construct BDAC. The literature review points out three building blocks for BDA: BDA technology capability, BDA management capability and BDA talent capability (Akter et al., 2016; Yasmin et al., 2020). BDA management capability refers to organisational capacity, BDA technical capability refers to the firm's physical infrastructure strength, and BDA talent capability refers to the organisational human knowledge capital (Kiron et al., 2014; Wamba et al., 2017). Apart from BDAC's established three building blocks, several investigations theorise two other intangible characteristics of BDAC: 'data-driven culture' and 'the intensity of organisational learning (Arunachalam et al., 2018). Hence, there still is no settled theory for the measurement of

BDAC. In this proposed study, the BDAC construct is formed as a modified combination of three sub-constructs originating from the BDAC model proposed by Wamba et al. (Wamba et al., 2017) and followed by Mikalef, Boura, et al. (Mikalef, Boura, et al., 2020; Shamim et al., 2020) and Shamim et al (Mikalef, Boura, et al., 2020; Shamim et al., 2020).

Studies found a significant positive effect between BDACs and a firm's economic performance (Aziz et al., 2024; Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Faridoon et al., 2024; Jantaro & Badir, 2024; León et al., 2024; Orero-Blat et al., 2024; Ottou et al., 2024; Yasmin et al., 2020; Zhou et al., 2024). Another investigation found a significant positive correlation between predictive analytics capabilities and supply chain sustainability performance (Jeble et al., 2018). To further expand on the impact of BDAC, recent studies highlight the importance of fostering a data-driven organisational culture as a catalyst for enhancing BDA's efficacy in achieving sustainability goals. Developing a robust data-driven culture empowers decision-makers to embrace evidence-based approaches, which are integral for optimising resource utilisation and minimising waste across supply chains (Al-Khatib & Ramayah, 2023; Fantazy & Tipu, 2023; Liu et al., 2023; Tipu & Fantazy, 2023). Furthermore, organisations that cultivate continuous learning and encourage employees to enhance their analytical skills are better positioned to leverage BDA insights, thereby contributing positively to sustainability across economic, social, and environmental dimensions (C.-h. Chen, 2022; Chen & Chen, 2021; Syafrizal et al., 2023; Upadhyay & Kumar, 2020).

The role of BDAC in addressing social sustainability is underscored by its capacity to improve transparency and ethical standards within the supply chain. By enabling real-time monitoring and reporting, BDAC helps organisations identify and mitigate unethical practices, such as labour violations or unfair pricing, thus fostering a socially responsible supply chain (Khokhar et al., 2020; Kumar & Anbanandam, 2020, 2022). Additionally, recent research emphasises that BDAC can support inclusivity by analysing workforce demographics, thereby enabling organisations to take proactive steps toward equity and diversity goals (Choi & Park, 2022; Venkatesh Mani et al., 2016; Sodero et al., 2019; Wang et al., 2020; Yıldızbaşı et al., 2020) (Farias & Costa, 2023). In relation to the environment, BDAC facilitates predictive modelling and advanced analytics, which are essential for managing resource flows in ways that reduce ecological impact. For instance, organisations can leverage BDAC to design circular economy models by predicting resource lifecycles and optimising recycling processes, and such innovations allow firms to meet environmental targets while simultaneously reducing costs

associated with raw material consumption and waste disposal (Banyai et al., 2019; Janik-Karpinska et al., 2023; Mandičák et al., 2021; Olivares-Tirado & Zanga, 2024).

Moreover, recent advances in machine learning and artificial intelligence are creating new opportunities for BDAC to enhance organisational resilience and adaptability, particularly in dynamic industries like healthcare, where swift responses to changes in demand or supply chain disruptions are critical (Collins et al., 2021; Dubey, Gunasekaran, et al., 2020; Guida et al., 2023; Machiani et al., 2024; Zhang et al., 2020). This flexibility, enabled by BDAC, allows firms to adjust operations quickly, ensuring sustained performance across the triple bottom line: people, planet, and profit (Aziz et al., 2024; Kusonkhum et al., 2023; Mesquita et al., 2023; Motaung & Sifolo, 2023; Said et al., 2023) (Kamal et al., 2024).

Ultimately, the expanding research on BDAC demonstrates a broadening focus on integrating data analytics within organisational cultures and capabilities, moving beyond the foundational elements of technology, management, and talent toward a holistic adoption that aligns with global sustainability standards. As organisations continue to embed BDA insights into strategic decision-making processes, they will be better equipped to meet sustainability goals and gain a competitive advantage by prioritising long-term value creation over short-term financial gains (Chalmeta & Barqueros-Muñoz, 2021; Mesquita et al., 2023; Raut, Mangla, et al., 2021; Said et al., 2023; Zhu & Yang, 2021). This alignment with sustainability principles underscores the transformative potential of BDAC for achieving sustained organisational growth while addressing broader social and environmental concerns.

Based on the previous academic findings and practitioner literature, I hypothesised that the BDAC positively influences the sustainability performance of the healthcare supply chain. Thus, I formulated the following hypothesis.

H1: BDAC positively influences the sustainability performance of the healthcare supply chain.

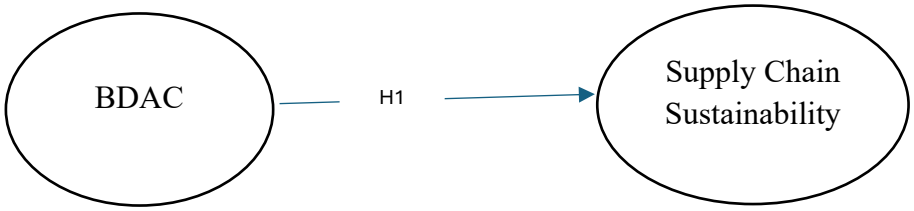



Figure 3.1 Hypothesis H1

### 3.3 BDAC and Public Procurement Optimisation

Since the birth of any firm, procurement has become part and parcel of any organisation (Altundag & Wynn, 2024; Arve & Zwart, 2023; Liu et al., 2023; Soylu, Corcho, Elvesæter, Badenes-Olmedo, Yedro-Martínez, et al., 2022). An empirical study in the USA and Italy found that BDA adoption in procurement improves internal procurement performance by optimising lead time, cost, quality, and flexibility (Moretto et al., 2017). Another empirical study, mainly examining European and American companies, found that artificial intelligence, BDA, and the IoT are three core elements for future procurement automation processes, which will create more space for strategic initiatives driven by humans (Bienhaus & Haddud, 2018). Another recent empirical study found that advanced technology like BDA optimises procurement (Bag, Wood, Mangla, & Luthra, 2020). Besides, there are reports of a significant relationship between BDAC and e-procurement (Bader Khamis AlNuaimi et al., 2021). However, in developing countries, such studies were limited, and traditional legal supervision is only prominent in the procurement process, eventually proving ineffectual. For instance, a recent study on Uganda's healthcare revealed that even after a drastic increase in oversight and supervision of public spending, a long-term positive result still needed to be achieved (Peiffer et al., 2018). Moreover, a wrongdoer utilises the latest technologies to shun detection (Dávid-Barrett & Fazekas, 2020; Hagan, 2017). Recent studies reported mafia infiltration to prevent more capable and efficient firms from winning the contract (Ravenda et al., 2020). The procuring entities must have technological capabilities to outshine the wrongdoers' any such ill-willed moves. It, in turn, will ensure value for money utilised from public funds.

However, academic research on procurement analytics is still nascent, and most prior studies focused on solutions based on structured data (Handfield et al., 2019). The same USA-based survey revealed that there needs to be higher usage of advanced procurement analytics, and two major issues preventing the low advances in analytics are data integrity and quality. These research outcomes support our literature findings that very few studies focused on the developing country contexts where technology adoption is limited. Nevertheless, a few research studies that focused on developing country contexts have confirmed the positive impacts of integrating the latest technology in the procurement ecosystem. For instance, research on public procurement contracts data of Columbia from 2011 to 2015 suggests an early warning model for early detection of inefficiency and wrongdoings in procurement using technology (Gallego et al., 2021). This study utilised machine learning modes to predict inefficiencies in public procurement and found net positive impacts. Another study based on

Malaysia's public sector healthcare procurement revealed that the country's public health sector purchased different medicines at two to three times the international reference price (IRP) (Hamzah et al., 2020). It concluded that existing procurement mechanisms failed to achieve optimised value for money medicine sourcing by balancing between ensuring competitive procurement prices and adherence to national procurement policies. Technology such as BDA can help the concerned authority in dynamic price checks to source medicine at the IRP. Thus, more research is required on the impact of BDAC on procurement optimisation in the context of developing countries and critical sectors such as healthcare.

BDAC can revolutionise public procurement optimisation, particularly by addressing longstanding challenges in transparency, decision-making accuracy, and responsiveness to emerging market conditions. The integration of BDAC into procurement processes can help identify and analyse patterns in vast amounts of structured and unstructured data, which has profound implications for public procurement in complex and regulated sectors like healthcare. This shift towards data-driven procurement offers potential for improved sourcing, supplier selection, and strategic resource allocation, enhancing the overall efficiency of procurement practices (Altundag & Wynn, 2024; Harju et al., 2023; Jantaro & Badir, 2024; Mavidis et al., 2024; Shao et al., 2022; J. Zhang et al., 2022a).

For instance, recent studies in public sector procurement highlight how BDAC can enhance supplier performance tracking and mitigate risks associated with supply chain disruptions. Recent studies in the logistics sector revealed that BDAC enables real-time data sharing and predictive analytics, helping procurement teams forecast supply needs and pre-emptively address disruptions, which could be particularly beneficial in the healthcare sector with its strict requirements and sensitivity to supply chain continuity (Benzidia et al., 2023; Benzidia et al., 2021). Additionally, BDAC allows for the assessment of supplier compliance with contractual and ethical standards, an area that remains critical for public healthcare entities that depend on reliable, quality-driven suppliers (Bader Khamis AlNuaimi et al., 2021; Faridoon et al., 2024; Shokouhyar et al., 2020).

Beyond enhancing efficiency, BDAC can address procurement fraud, an issue frequently exacerbated by limited oversight capabilities in public sector systems. Machine learning algorithms, for instance, can flag anomalies that indicate potential misconduct, such as irregular pricing patterns or unusually rapid supplier changes (Altundag & Wynn, 2024; Barajei et al.,

2023; Chen et al., 2024; Colque-Diaz et al., 2024; Decarolis & Giorgiantonio, 2022; Soylu, Corcho, Elvesæter, Badenes-Olmedo, Yedro-Martínez, et al., 2022). In sectors such as healthcare, where procurement involves a high volume of transactions across numerous vendors, these analytics can reduce risk by improving transparency and accountability within procurement cycles.

Despite these advances, procurement in developing countries faces unique challenges that can affect BDAC implementation, such as data silos, outdated IT infrastructures, and insufficient digital skills among procurement officers. Thus, while the potential benefits of BDAC in procurement optimisation are significant, developing nations may require targeted strategies to address such barriers. Researches underscore that capacity-building efforts, government support, and phased implementation of BDAC technologies are essential steps for enabling the successful adoption and utilisation of advanced analytics in public procurement (Del Sarto et al., 2024; Govindan et al., 2024; Guida et al., 2023; Hm et al., 2024; Liao et al., 2024; Rizky et al., 2023; Sun et al., 2024; J. Zhang et al., 2022a).

In healthcare, where procurement inefficiencies can have far-reaching consequences, BDAC enables data-informed decisions and strengthens procurement adaptability in response to public health demands. A study conducted on pandemic preparedness in the healthcare sector, for instance, found that BDAC facilitated a more rapid response to fluctuating supply demands, reducing stockouts and ensuring the availability of critical supplies. By optimising procurement processes, BDAC supports resilience-building in healthcare supply chains, a factor that has gained increased importance following the COVID-19 pandemic (Behl et al., 2022; Chytilová et al., 2024; Khalil et al., 2023; Machiani et al., 2024; Sathiya et al., 2023; Sharma et al., 2021; Sheng et al., 2020; Wided, 2023).

The literature suggests that the successful adoption of BDAC in public procurement within healthcare not only optimises immediate outcomes but also creates a foundation for ongoing improvements in data governance, compliance tracking, and resource allocation efficiency. As developing nations explore these tools, more research is needed to evaluate and document specific BDAC-driven outcomes, especially under diverse socioeconomic conditions. This will provide a clearer understanding of how BDAC can be scaled effectively to optimise procurement in critical public sectors globally.

Based on the empirical evidence and theoretical arguments above, I formulated H2 to find a causal relationship between BDAC and the optimisation of public healthcare procurement.

**H2:** BDAC has a direct positive impact on "Procurement Optimisation"

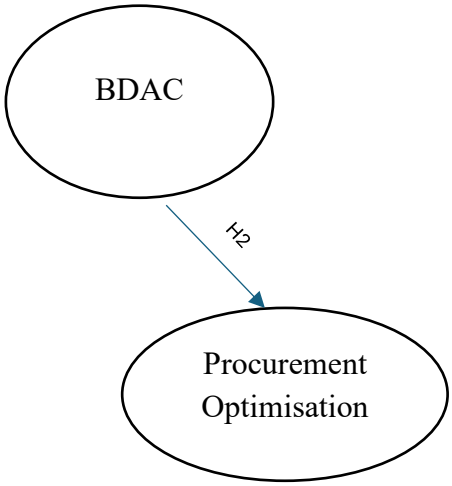



Figure 3.2 Hypothesis H2

### 3.4 Public Procurement Optimisation and Supply Chain Sustainability

One of the core pillars of our thesis is BDAC, which is hypothesised in the earlier section as a positive contributor to procurement optimisation and sustainability. In this section, I aim to establish the hypothetical causal link between procurement optimisation and sustainability performance.

It is empirically shown that the optimisation of various business processes contributes to sustainability. A significant number of empirical evidence is available confirming the positive impact of optimising business functions toward improving sustainability performance (Adlane & Aouane, 2020; Choi, 2022; Choi et al., 2017; Gibson et al., 2019; Kovács & Illés, 2019; Palander & Vesa, 2022; Phalake et al., 2023; Scholz et al., 2018). It is also reported that optimisation significantly impacts overall supply chain sustainability (Beheshtinia et al., 2021). Particularly under any uncertain situation, optimisation helps to improve supply chain sustainability performance (Li et al., 2022).

In the post-COVID time with looming uncertainties in many sectors, global firms, particularly in the sectors hard hit by COVID-19, such as tourism and health, need optimisation. A study found that innovative technology can help tourism sector optimisation and thus achieve higher sustainability performance (Eddyono et al., 2021). In essential services such as water supply, it is empirically tested that optimisation helps improve sustainability performance (Gibson et

al., 2019). Therefore, I hypothesised that procurement optimisation, an essential business process, can also impact healthcare supply chain sustainability performance.

A few investigations recently confirmed that disrupting technologies can significantly impact the optimisation process to improve sustainability performance. Technology such as Blockchain positively contributes sustainably through optimisation (Choi, 2022). Industry 4.0 technology directly impacts sustainability by optimising business processes (Banyai et al., 2019).

There is a tendency to use procurement optimisation and optimal supplier selection interchangeably. The problem associated with best supplier selections has been studied previously. A significant count of empirical studies on supplier selection has been published. Even prior to the supply chain becoming a research theme, supplier or vendor selection had been addressed by many studies. For instance, the earliest vendor selection study can be referred back to 1960 (Raj Singh et al., 2024). However, procurement optimisation is more than just selecting the best supplier; it is comparatively less studied (Ershadi et al., 2021; Grandia & Kruyen, 2020; Mircea et al., 2022; Osmonbekov & Johnston, 2018; J. Zhang et al., 2019).

Supplier selection decision criteria are mainly focused on the best deal. On the other hand, procurement optimisation depends on the best supplier selection and the best utilisation of procured goods/services by the procuring entity. Thus, procurement optimisation directly impacts overall supply chain resilience (Kaur et al., 2020). Internal utilisation capacity, such as resource mobilisation, significantly affects the optimal use of procured goods or services (Barrad et al., 2020; Garcia Rodriguez et al., 2021; García Rodríguez et al., 2020; Palander & Vesa, 2022). Thus, the need for responsible procurement, which recognises the three pillars of sustainability, emerges. Optimised utilisation of organisational resources is pivotal in ensuring sustainability (Badiezadeh et al., 2018; Chowdhury et al., 2020; Marcis et al., 2019; Moore et al., 2017; Vivas et al., 2019). While optimisation of procurement has a direct influence on supply chain sustainability (Evangelista & Hallikas, 2022), a recent study found that e-procurement optimises the supply chain and thus increases the sustainability performance of the supply chain (Singh & Chan, 2022).

These studies espouse that even if the best supplier is selected, the optimal use of the resources needs to be planned and executed; otherwise, procurement optimisation will not be achieved. This phenomenon is even more evident in a complex industry, such as healthcare, where procured goods or services utilisation depends on many just in time intertwined other resources

availability (Ageron et al., 2018; Heath, 2020; lo Storto & Goncharuk, 2017; Moro Visconti & Morea, 2019; Strang & Sun, 2020). For instance, the best low-cost procurement deal can be made with the best supplier selection decision framework for procuring hospital equipment. However, the maximum utilisation of procured equipment depends on the allocation/reallocation of the product within the hospital supply chain. Therefore, procurement optimisation performance measurement is more complicated than supplier selection issues. Quantifying the indicators to measure the optimal yield from any procurement process is complex. If hospital supplies are procured more than required, it would have an economic and environmental impact.

The theory of auctions and competitive bidding is the most frequently used theory in public procurement research (Flynn & Davis, 2014), which advocates optimal sourcing. Researchers utilised various techniques in determining optimum decisions that yield the most utility. One of those methods is the Influence Diagramram (IDs) method. IDs are competent in solving challenging problems such as complex procurement and uncertainties. A recent study based on the IDs technique has used three KPIs: procurement cycle time, supplier performance, and staff training (Abolbashari et al., 2018).

Although there was no order of preference, the researchers began formulating a set of criteria in the early sixties. A couple of years later, different supplier selections and prioritisation of selection criteria emerged when, in 1966, Dickson proposed 23 performance evaluation criteria (Hlyal et al., 2015). Those criteria were empirically tested, and the most critical performance measurement indicators in evaluating suppliers were quality, skills, delivery, warranty and price. However, the importance of the proposed 23 indicators changed occasionally. An early ninety's study showed that the most crucial indicators were price, delivery, quantity, production capacity and geographic location (Weber et al., 1991). A few years later, another study surveying 323 companies found four critical criteria: quality, price, delivery, and flexibility (Verma & Pullman, 1998). Hence, it is implied that KPIs of supplier selections or even procurement optimisation are subject to change and are sector-specific. A study on public procurement found that in procurement performance measurement, efficiency and cost KPIs are predominant, and more than 45% of measures are related to these two dimensions (Patrucco et al., 2016). This finding is justified as these two areas are monitored and controlled in public sector procurement, where optimal public resource use is essential (Chan & Karim, 2012). The

existing empirical evidence also supports that cost optimisation and quality directly link supply chain sustainability.

The second part of our investigation is to identify the causal relationship between the optimisation of public procurement and the supply chain's sustainability performance.

While substantial research focused on the operational and environmental advantages of procurement optimisation, recent studies suggest that this optimisation plays a critical role in fostering resilience within the healthcare sector. By implementing a strategic approach to procurement, organisations can address both demand fluctuations and resource constraints, which are especially crucial in healthcare. Studies show that proactive procurement strategies in healthcare directly contribute to building resilient supply chains capable of adapting to sudden shocks, such as supply shortages or increased demand (Del Sarto et al., 2024; Etse et al., 2021; Rai et al., 2024). This resilience, in turn, strengthens the supply chain's sustainability by mitigating risk and reducing waste through efficient resource allocation.

In addition to direct sustainability-related outcomes, procurement optimisation has been increasingly tied to broader economic impacts. For instance, optimising procurement processes in healthcare not only improves cost efficiency but also ensures equitable access to necessary resources, particularly in publicly funded systems where budget constraints are stringent (Adlane & Aouane, 2020; Khatun et al., 2024). Such impacts align procurement with the three pillars of sustainability—economic, environmental, and social—demonstrating that optimised procurement strategies can deliver value beyond operational metrics.

### 3.4.1 Technological innovation and enhanced procurement efficiency

Emerging technologies have transformed procurement optimisation from a primarily transactional function to a strategic one. For instance, artificial intelligence (AI) and predictive analytics offer new possibilities for real-time decision-making in supplier selection, inventory management, and demand forecasting, allowing organisations to respond dynamically to changing conditions (Altundag & Wynn, 2024; Andrade et al., 2024; Chytilová et al., 2024; Govindan et al., 2024; Hm et al., 2024). Studies in digital procurement also underscore the role of automation in reducing human error and inefficiency, streamlining procurement cycles, and minimising excess inventory (Chytilová et al., 2024; Govindan et al., 2024; Hm et al., 2024;

Ibrahim et al., 2023; Rai et al., 2024; Rizky et al., 2023; Siciliani et al., 2023). These technologies not only optimise procurement but also contribute to sustainability by enabling resource-efficient practices and reducing the environmental footprint.

Moreover, smart contracts and blockchain have emerged as valuable tools for enhancing transparency in procurement activities and reducing risks related to fraud and contract disputes. By integrating blockchain into procurement processes, organisations can achieve greater traceability, ensuring that every stage of procurement aligns with sustainability goals (Amiri Ara et al., 2021; Govindan et al., 2024; Khalfan et al., 2022; Rai et al., 2024). Although nascent, blockchain's application in healthcare procurement shows promise in enhancing accountability and ensuring that sustainable practices are adhered to at every level of the supply chain.

### 3.4.2 Sector-specific optimisation metrics in healthcare procurement

The healthcare sector's unique requirements demand specialised metrics and key performance indicators (KPIs) that differ from those used in general procurement optimisation. Metrics such as equipment utilisation rates, lead times for critical medical supplies, and regulatory compliance rates are particularly relevant in assessing procurement efficiency within healthcare settings. Recent research indicated that procurement optimisation metrics should prioritise health outcomes and patient care alongside traditional metrics like cost and delivery times (Gopal et al., 2019; Kim & Kim, 2019; Wolfenden et al., 2019). As such, optimising procurement in healthcare settings calls for a balanced approach that considers the sector's unique ethical and logistical challenges.

### 3.4.3 Role of public procurement policies in supporting sustainable practices

Lastly, public procurement policies have a considerable impact on sustainability, particularly in sectors such as healthcare, where procurement decisions often involve substantial public resources. Policies promoting sustainable procurement practices encourage organisations to select suppliers who adhere to environmentally responsible practices and to prioritise goods that are reusable, recyclable, or biodegradable. By incorporating sustainability-driven criteria into public procurement frameworks, healthcare organisations can contribute significantly to environmental goals while achieving cost efficiencies (Bevere & Faccilongo, 2024; Daú et al., 2019; Del Sarto et al., 2024; Moro Visconti & Morea, 2019; Rodriguez et al., 2019). In developing countries, policy-driven optimization strategies can help address limitations in

procurement processes, such as limited supplier availability or inconsistent supply, enhancing overall supply chain sustainability and resource stewardship.

Considering the existing literature and empirical evidence, I was motivated to explore the empirical evidence between procurement optimisation and supply chain sustainability performance in a developing country context. Thus, I formulated hypothesis H3.

**H3:** Procurement optimisation has a direct positive impact on the sustainability performance of the supply chain.

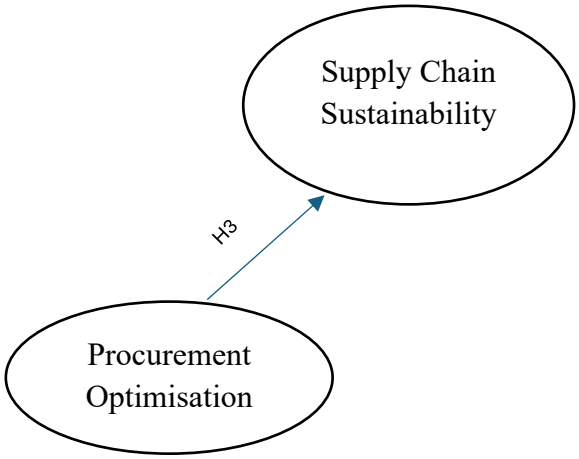



Figure 3.3 Hypothesis H3

The following conceptual research framework is formed through the integration of all three hypotheses into a single, integrated framework.

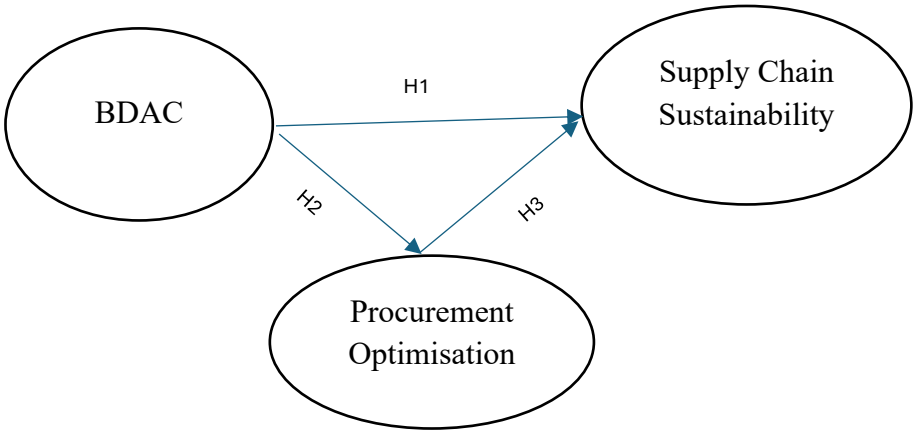



Figure 3.4 Research framework

# 4. Research Methods

The research design of any research project is considered to present the blueprint for the concerned investigation, thus providing a guiding framework. This framework facilitates the researcher to answer the research questions of the concerned research (Cooper & Schindler, 2014). Also, research design ensures that the data collected for the investigation is sufficient in quantity and can answer research questions in a clear manner (Vogt, 2010). Therefore, it provides a clear roadmap for the achievement of the objectives of any investigation while providing a reasonable flowchart of processes to be exercised and informing the development of hypotheses.

A fundamental component of any research design is the research methodology that is to be utilised, which falls under the adopted research design (Bell et al., 2018). The determination of the appropriate research methods to be utilised in the conduction of a given research is, therefore, an important step forward. The selection of appropriate research methods helps researchers collect data effectively and solve the problem in question (Rajasekar et al., 2013). This research predominantly employed a quantitative method of study through the conduction of a survey. This chapter formulates the research design and methodology that are to be utilised in this research. It also describes the rationale behind the data collection method and the measures that are adopted in attempting to minimise potential common method biases. Besides, it also discusses the ways the latent constructs are developed and measured.

## 4.1 Research Paradigm

The word ‘paradigm’ is derived from the Latin word 'paradigma', which appears in Greek as 'paradeigma' (Kankam, 2019). The research paradigm, also called as ‘research philosophy’, is a system of beliefs and assumptions in the knowledge development process in which investigators position their research pursuits (Saunders et al., 2019). Thus, the research paradigm entails critical assumptions affecting a researcher's perception of the real world and the way it explores the answers to the research questions developed. These assumptions are pivotal in choosing appropriate research methods with a befitting research strategy and data collection methods (Saunders et al., 2019). These assumptions eventually make the research design for any investigation and provide a guiding framework to conduct the research. The framework then helps the researchers to answer the research questions of the investigations based on the research philosophy chosen (Cooper & Schindler, 2014).

The two most settled research philosophies in social science research are interpretivism and positivism (Tsang, 2014). Interpretivism philosophy talks about exploring the fact of having different perceptions and encounters among individuals (Easterby-Smith et al., 2002). Therefore, the foundation of this paradigm is based on the major belief that the investigation is driven by the interpretation of researchers on their research material, beliefs and values (Saunders et al., 2019). It is strongly believed that interpretivism can deeply dive into the complexity of social behaviour and generate accurate insights (Irshaidat, 2019). Interpretivism is driven by constructivist ontology and thus relies on the perception that social surroundings are not given but rather constructed and imposed by humans (Irshaidat, 2019). Therefore, the interpretivism paradigm rejects the existence of any fixed facts and detached entities.

The interpretive approach usually adopts a qualitative research method focusing on human interaction or social phenomena (Creswell et al., 2003). Interpretivists advocate a humanistic or empathic attitude and utilise the social actors' subjective look out of the social reality (Saunders et al., 2019). There is a notion that considers that social science's subject matters and associated people and their institutions fundamentally differ from those of natural sciences (Bell & Bryman, 2007; Bell et al., 2018). Based on this contention, the interpretative paradigm affirms that social science is very complicated, as it differs from physical science (Saunders et al., 2019); therefore, it isn't easy to study through assumptions and scientific interpretation. Therefore, interpretivists researchers often adopt a more flexible research structure, more inclined to personal beliefs (Carson et al., 2001). Such a customised approach is more responsive in capturing insights from human interactions than the positivist approach, underpinned by rigid structural frameworks (Irshaidat, 2019; Sanchez et al., 2022).

Despite having many differences, both approaches have some similarities, too. For instance, even though advocates of both approaches' understanding of patterns of truth are far from identical, both interpretivists and positivists believe in the existence of patterns (Sanchez et al., 2022).

Positivism is more about generating new hypotheses based on existing knowledge and demonstrating the accurate, objective facts of an individual's behaviour to confirm the validity of theories (Irshaidat, 2019; Kreuger & Neuman, 2006; Marc, 2020; Neuman, 2006). One of the salient philosophical features of positivism is exploring and understanding the actual human

behaviour and interpreting the sense accurately instead of predicting the causes and effects (Neuman, 2006). From an ontological point of view, positivists' underlying assumption is "reality". Therefore, positivism studies any social phenomenon by embracing an objective stance using a logical and rational approach (Carson et al., 2001). In doing so, positivism hypothesises that a phenomenon is understandable through models that establish true explanations independent of the observer's perception (Sanchez et al., 2022). The models include different constructs and variables connected through a generalisable cause-effect mechanism, which can be tested empirically (Irshaidat, 2019; Sanchez et al., 2022). As a logical consequence, positivism relies more on quantifiable observations, leading to statistical modelling and analysis. The positivist paradigm interprets observation (the senses) using logical and statistical operations and provides information and positive facts (verified data) as output (Saunders et al., 2019); thus, findings are usually quantifiable and observable. Positivism adheres to the assumption that only "factual" knowledge attained through observation is trustworthy; therefore, in a positivism-led investigation, the role of researchers is limited to quality data collection and appropriate interpretation of results objectively (Irshaidat, 2019; Sanchez et al., 2022). Therefore, researchers must adopt the best approach to collect positive information or facts about the phenomenon (Bell & Bryman, 2007; Bell et al., 2018).

The positivist approach adopts research models and hypotheses based on quantitatively measurable independent facts (Bell et al., 2018). Understanding the hypothetical issues guiding the exploration of worldview helps empower the creation of attractive outcomes resulting from research activities (Easterby-Smith et al., 2002).

This study explores the relationships between numerous factors in the context of big data analytics capabilities and the sustainability performance of the healthcare supply chain. The study falls into a social research category. Therefore, it can broadly adopt either a positivism or interpretivist approach to investigation. This study is positioned within a positivist paradigm, considering previous reviews of different philosophical positions in social science research. The positivist paradigm has been applied to our investigation through the quantitative method. The quantitative approach adopts an actual data-examining strategy and interprets the information as statistical outcomes; therefore, findings are summed up to a wider population (Mitchell & Bernauer, 2016). Therefore, I utilised a quantitative approach as the research technique best fit to deal with the positivism paradigm as accurately as could practically be

estimated by an issue under scrutiny (Kreuger & Neuman, 2006). I was convinced that the knowledge of research "out there" and in the empirical sites (real world) can be observed (Creswell et al., 2003; Rajasekar et al., 2013; Saunders et al., 2019). The reality of this investigation was depicted by real objects such as "procurement optimisation performance", the formation of "Big data analytics capabilities", "Social Performance", "Economic Performance", "Environmental Performance", etc. As the main objective of this research is to conduct an empirical investigation based on real data, taking a positivist paradigm as my research approach is justified (Bell et al., 2018; Cooper & Schindler, 2014; Kreuger & Neuman, 2006; Marc, 2020; Neuman, 2006; Rajasekar et al., 2013; Saunders et al., 2019).

Thus, the philosophical stance of this thesis is aligned with the 'Positivist Paradigm'. It begins with the building of a rational model and theories. Then, I framed relevant hypotheses, extracted relevant literature, and evaluated them in a positivist way. I quantitatively analysed the rational model to interpret the persistent concerns in the research context. A study technique is thus applied to derive the final model.

Quantitative research involves collecting numerical data and using statistical methods to analyse it. This type of research is often used in the natural and social sciences and can be used to test hypotheses, measure variables, and make predictions (Bell et al., 2018; Cooper & Schindler, 2014; Creswell et al., 2003; Rajasekar et al., 2013; Saunders et al., 2019). Some examples of quantitative research approaches include surveys, experiments, and observational studies. This investigation used surveys as the primary means of collecting numerical data. A survey gathers information about a population by asking standardised questions to a set of individuals (Bell et al., 2018; Cooper & Schindler, 2014; Creswell et al., 2003). This survey effectively gathers quantifiable information about attitudes, beliefs and behaviours towards any real phenomenon (Bell et al., 2018; Cooper & Schindler, 2014). A researcher can administer a survey in different ways, such as in person, by phone, online, etc. We used a couple of means, explained in the following sections, to reach the right respondents.

In light of the above discussion, it is evident that positivism is pertinent to the explanatory targeted aim of any investigation to grasp the causal relationship (Saunders et al., 2019). It helps develop a research model and connect appropriate theories to this model. This study paradigm, i.e., positivism, directed this investigation to select the best study methodology,

including but not limited to research strategy and data collection methods. These are discussed in the following sections.

### 4.2 Research Design

Research design is a plan or blueprint for conducting research (Rajasekar et al., 2013; Saunders et al., 2019). It outlines the methods and procedures for collecting and analysing data systematically and efficiently (Bell et al., 2018; L. Chen, 2022; Cooper & Schindler, 2014; Creswell et al., 2003). Therefore, the research design should be tailored to the specific research question and data collection type.

Several research design approaches exist, such as experimental, observational, and survey designs. Regardless of the research design chosen, the researcher needs to be clear about some fundamental research components. Those are but are not limited to the research question, the hypotheses being tested, and the methods and procedures for collecting and analysing data (Kreuger & Neuman, 2006; Saunders et al., 2019; Vogt, 2010). The research design should also be reviewed and approved by an institutional review board (IRB) to ensure it adheres to ethical standards for conducting research with human participants.

One of the fundamental and introductory steps of research design in social science is identifying the best-fit reasoning or research approach for the investigation. This approach must be aligned with the chosen research paradigm (Bell et al., 2018; Cooper & Schindler, 2014). Deductive, inductive, and abductive are three different broad approaches to reasoning and making inferences in a social science context.

Deductive reasoning starts with a general statement or hypothesis and then applies logical reasoning to reach a specific conclusion. This approach is the most reliable because the conclusion must be true if the initial statement and the reasoning are valid. For instance, if all men are mortal and Socrates is a man, it logically follows that Socrates is mortal.

Inductive reasoning, on the other hand, starts with specific observations or evidence and then uses that information to make a generalisation or prediction (Collis & Hussey, 2014). This approach is less reliable than deductive reasoning because it is based on patterns or trends that may only sometimes hold true (Bell et al., 2018; Saunders et al., 2019; Vogt, 2010). For

instance, if a person observes that it has rained every day for the past week, they may make the inductive inference that it will rain tomorrow, which may not happen at all.

Abductive reasoning starts with an incomplete set of observations or evidence and uses that information to come up with the best possible explanation (Cooper & Schindler, 2014; Saunders et al., 2019). This approach is often utilised in scientific research and problem-solving and is considered a combination of deductive and inductive reasoning. For instance, if a person observes that a plant is wilting, they may use abductive reasoning to infer that it needs water based on the best explanation for the observed symptoms.

In summary, 'deductive reasoning' is rooted in logical reasoning, 'inductive reasoning' is based on observations and evidence, and 'abductive reasoning' is based on the best explanation for a given set of observations and evidence. Each approach has advantages and limitations, and the choice of which approach depends on the problem or question to be addressed.

Our research design starts with finalising the right reasoning approach in line with our chosen 'Positivism Paradigm'. The best-fit reasoning for the nature of our investigation is the deductive reasoning approach. Deductive reasoning is a top-down, structured technique, often referred to as "moving from the general to the particular" (Collis & Hussey, 2014); it starts with a broad theory and empirically investigates the developed hypotheses. Another salient feature that makes deductive reasoning the best fit for our research is that it emphasises cause-effect relations and follows both the 'positivism paradigm' and 'quantitative research' techniques (David & Sutton, 2011). In our study, the deductive reasoning approach supports theoretical positioning and testing of the existing body of knowledge on BDAC, procurement optimisation, and SSCP. The process involved creating a theoretical framework based on empirical input and testing the hypotheses developed (Bell et al., 2018; Cooper & Schindler, 2014; Creswell et al., 2003; Vogt, 2010). I identified numerous studies relevant to this research context that similarly employed quantitative techniques and deductive reasoning for theory testing (Bag, Dhamija, et al., 2020; Bag et al., 2021a; Bag, Wood, Mangla, & Luthra, 2020; Bag, Wood, Xu, et al., 2020; Cunha, 2018; Dubey, Gunasekaran, & Childe, 2019; Dubey, Gunasekaran, et al., 2020; Dubey, Gunasekaran, Childe, Roubaud, et al., 2019; Edwin Cheng et al., 2021; Mandal, 2018, 2019; Oncioiu et al., 2019; Queiroz & Telles, 2018; Raut et al., 2018; Raut, Mangla, et al., 2021; Raut et al., 2019; Raut, Yadav, et al., 2021; Shokouhyar et al., 2020; Telukdarie et al., 2018).

In conducting this research, I systematically followed all six fundamental chronological steps of deductive reasoning as outlined by (Bell et al., 2018).

i) Theory
ii) Hypothesis
iii) Data Collection [Includes questionnaire development if applicable]
iv) Findings
v) Confirmation or rejection of a hypothesis
vi) Revision of the theory from the final model

### 4.3 Research Strategy

A research strategy is a plan of action that outlines the methods and techniques used to conduct a research investigation (Vogt, 2010). It is an essential part of any research project, as it guides the researcher in collecting and analysing data (Neuman, 2006; Saunders et al., 2019).

One of the initial steps in developing a research strategy is to define the research question. The research question should be clear and specific, and it should be something that can be answered through the collection and analysis of data (Bell et al., 2018; Cooper & Schindler, 2014). Once a research question has been defined, the researcher can begin to develop a plan for data collection and analysis.

Several methods can be utilised to collect data for a research project, including surveys, interviews, case studies, action research, grounded theory, observations, and experiments (Kreuger & Neuman, 2006; Saunders et al., 2019; Vogt, 2010). The choice of method will depend on the ability to answer the research question, the ability to achieve the research objectives, the availability and extent of existing knowledge, the population being studied, and the resources available. For example, if the research question is about the opinions of a specific group of people, a survey may be the best method (Creswell et al., 2003; Kreuger & Neuman, 2006; Preacher & Hayes, 2004). If the research question is about the behaviour of a specific group of people, an observation may be the best method.

Data analysis is the process of interpreting the data that has been collected. Several different techniques can be used to analyse data, including statistical analysis, content analysis, and thematic analysis. The choice of technique will depend on the research question and the type of data that has been collected. Once the data has been collected and analysed, the researcher

can draw conclusions and make recommendations. The conclusions and recommendations should be based on the data that has been collected, and they should be supported by evidence.

Thus, it is consensually agreed by researchers that a research strategy is essential to any research project to achieve the research objectives (Cooper & Schindler, 2014). It guides a researcher in collecting and analysing data and helps ensure the research question is answered thoroughly and meaningfully. Therefore, a well-developed research strategy is essential for the success of any research project.

This investigation has adopted two 'research strategies' to answer the research question and achieve the research objectives. These are systematic literature reviews (SLR) and surveys.

The existing body of knowledge in the chosen research context has a phenomenal contribution to a head start in any research investigation (Saunders et al., 2019; Vogt, 2010). Therefore, this thesis aims to grasp prior research findings to identify the gaps and possible contribution aspects. My SLR's objective was to discover the existing body of knowledge in three core components of our research project. BDAC, "Public Procurement Optimisation", and "Sustainability Performance of the Healthcare Supply Chain" are those components. I have conducted the SLR to answer supplementary research questions:

1) What are the capabilities required to build BDAC?
2) In which sectors and countries has BDAC research expanded so far?
3) What issues (input/output/mediating/moderating variables) are empirically tested due to building BDAC?
4) What are the gaps for future research agendas related to BDAC and sustainability?

The SLR helped the research format three main constructs of our research framework. The SLR provided the baseline for developing all the previous chapter's hypotheses.

The core objective of this research is to develop a model to investigate the relationship among BDAC, PPO and SSC. As this study involves an empirical investigation of the causal relationship among constructs or research variables, explanatory type research is appropriate and pertinent to answer the main research questions. Explanatory research is preliminary research that clarifies the exact nature of the problem to be solved and is thus most aligned with the positivism paradigm (Bell et al., 2018; Saunders et al., 2019; Vogt, 2010). Therefore,

explanatory research has the most potential to provide an accurate answer to our following core research question, as presented in Chapter Two:

**R.Q.1.** How does BDAC enhance the 'sustainability performance' of the healthcare supply chain?

**R.Q.2.** Does procurement optimisation mediate the impact of BDAC on 'sustainability performance' of the healthcare supply chain?

> **R.Q.1.1.** How does BDAC facilitate the optimisation of public procurement in healthcare?
>
> **RQ 2.1.** How does the optimisation of public procurement affect the 'sustainability performance' of the healthcare supply chain?

This research employed a quantitative approach to answering the research questions and testing the hypotheses. As this study is explanatory in nature, the survey strategy is most consistent in the quantitative approach (Vogt, 2010). Survey strategy targets the research objectives within the boundary of a conceptual structure or theoretical context (Bell et al., 2018; Kreuger & Neuman, 2006). Therefore, the positivist paradigm, the philosophical stance of this research, is best reflected through the survey strategy (Saunders et al., 2019).

The SLR strategy, adopted for this investigation, has already been explained in detail in Chapter 2. The survey strategy has been explained in detail in the following sections.

## 4.4 Research Methods

### Survey and selection of the target population

This study adopted the survey strategy to collect numerical data from Bangladesh's big data and procurement stakeholders. The survey is the most appropriate method for collecting data for this study because it is the quickest and most reliable means of data collection and is most aligned with our research paradigm adopted. Considering the global pandemic, collecting empirical data from the field level was almost impossible without an online survey.

In business information system research, a survey is a widely used data collection approach (Bell et al., 2018). This research entails gathering information on a large group's characteristics, actions and opinions. A survey is the best approach for such extensively engaged data collection

(Saunders et al., 2019). This study explores the nature and associations between the constructs through an online cross-sectional survey.

As a plan B, a hard-copy questionnaire survey was also administered in limited cases [<= 20]. The survey invitation link was distributed among the different stakeholders. Invitation recipients include but are not limited to academicians, senior technology managers, procurement managers, IT officers, civil service officers, CPTU officials, and DGHS officials. Data collection took place in two phases. The primary phase was a pilot survey to test the suitability of the questionnaire and identify any possible issues. After completing the pilot survey, the final data collection was conducted from 1 June to 31 August 2022. The medium of the survey was English. This study adopted a previously validated instrument. It ensures that the measures are adequate and representative (Cooper & Schindler, 2014; Rajasekar et al., 2013). Participants completed a closed-ended questionnaire with 36 questions based on a five-point Likert scale ("strongly agree" = 5 to "strongly disagree" = 1). The five-point Likert scale is the most common practice for scaling responses in any survey design (Marc, 2020). The total response rate of the survey was 10.36%.

This study adopted a survey strategy rooted in deductive reasoning to test the hypotheses from empirical observation. Such an approach is widely used in testing causal relationships in real-life scenarios (Bell et al., 2018). Among the three principal data collection techniques, i) questionnaires, ii) structural observation and iii) structural interviews (Saunders et al., 2019), the questionnaire is the most common strategy for data collection. Approximately 84% of BDA researchers adopted questionnaire-driven surveys for data collection (Shdifat et al., 2019). For instance, some recent studies on BDA and BDAC chose a survey as the primary research method (Adiguzel et al., 2024; Aziz et al., 2024; Bag, Dhamija, et al., 2020; Bag, Wood, Xu, et al., 2020; El-Haddadeh et al., 2024; Faridoon et al., 2024; Feng et al., 2024; Hamzeh & Aburub, 2024; Ibrahim et al., 2024; Jeble et al., 2018; Khan et al., 2024; Khan & Fatima, 2024; León et al., 2024; Magableh et al., 2024; Orero-Blat et al., 2024; Pham & Vu, 2024; Raut, Mangla, et al., 2021; Riaz & Ali, 2024; Tongtong & Xinhang, 2024; Wang et al., 2024; Wu et al., 2024; Zan et al., 2024; Zhao et al., 2024; Zhou et al., 2024). The survey approach has three distinct advantages over other data collection methods. Firstly, the method attracts very limited financial commitment. Secondly, the survey is useful for retrieving data from different unobservable contexts such as preference, taste, belief, etc. Thirdly, as deductive reasoning is the basis of any survey, the method is most suitable for empirical understanding.

Although the survey is one of the most common research strategies in the SCM field (Soni & Kodali, 2012), it also has some challenges, such as high non-response rates, non-response bias and lack of required knowledge. The ways respondents are motivated to get their answers and complete the questionnaire also lead to response bias (Saunders et al., 2019). However, these challenges can be mitigated by considering how questions are asked and designed to capture specific constructs (Bloomfield et al., 2016) and employing appropriate statistical techniques (Hair Jr et al., 2017).

Having adequate subject-matter knowledge to answer all 36 questions was the prerequisite for our target respondents. This requirement was a challenge in finding a good number of experts. One possible option to overcome this challenge is to collect data from multiple people in an organisation, partially and then join all the feedback. Even though such a process has a chance to reduce the self-reporting bias, the approach is highly likely to result in low responses. So, we have carefully selected the participants with expertise in a) the use of any data analytics, b) procurement experience and c) sustainability awareness.

Currently, there is a countrywide advocacy programme running from the then Prime Minister's Office in Bangladesh to make people aware of UN SDG initiatives. Bangladesh's government made it mandatory to provide an SDG plan for every public service employee, which eventually helped us get respondents with experience in both data analytics and procurement with an acceptable understanding of the core sustainability concept. Therefore, our ideal targets are public-sector IT managers, public-sector technology suppliers, academics, senior bureaucrats, CEOs, and analytics professionals. A small portion of our respondents may need more technical knowledge of BDA. Therefore, a briefing was provided where necessary before the survey started. Only senior IT managers, Chief Information Officers, and mid to top-level managers were targeted to ensure respondents could answer all questions with strategic statistics. CIOs and senior IT officials were deemed capable of answering different performance indicator data. On top of all, our respondents had to have recent data analytics experience and have worked long enough with the organisation. More than 50% of respondents have at least eight years of experience. The questionnaire does not contain any questions requiring sensitive or classified information. We requested that the organisation's name be written to collect some publicly available financial information about that organisation and other public news regarding that company. We assured the participants that individual responses would not be published. An

aggregate result from the survey will be reported only, and there will be no trace of individual responses.

In the context of this study, conducted in a developing country, academics play a pivotal role in the adoption and diffusion of emerging technologies such as BDA. Unlike in developed economies, where industry often spearheads innovation, academia in developing regions frequently serves as a key source of early-stage conceptual development, research translation, and capacity-building. Their perspectives are therefore instrumental in shaping industry understanding and policy discourse around BDA integration. With regard to content validity, academic experts were included specifically during the pretesting phase of the survey instrument to evaluate clarity, relevance, and alignment with established theoretical constructs. This process, detailed in Chapter Five (Data Analysis), ensured the instrument's conceptual robustness and contextual appropriateness. Their participation was not intended to reflect the primary population under study but rather to enhance the methodological rigor and validity of the research design.

In consideration of our criteria, we sent the first email with a link to the online survey to 100 contacts in June 2022. We surveyed in multiple rounds to cover another 2070 contacts. We sent the final reminder on 15 August 2022. The survey took place across a span of 13 weeks. Previous research shows that online survey results have no statistical difference from paper surveys (Grandcolas et al., 2003). The survey covers stakeholders from multiple associated and related sub-sectors. Therefore, the generalisability of the research is more prominent than that of a survey conducted in a specific broad sector only.

My investigation endeavoured to link three independent research streams: BDAC, OPT and SSCP. Therefore, I have shortlisted our prospective respondents as executives/practitioners who have a moderate to expert-level understanding of all three sections of the questions. Although measuring a person's level of understanding is hard, I utilised a couple of primary selection criteria for finalising organisations and respondents.
To select a respondent, I utilised six criteria. a) Length of Service, b) Education Qualification, c) Experience in any technology department of any organisation or technology-related organisation, d) Experience in procurement, e) Experience in using any data analytics in real life and f) fundamental understanding of sustainability
I then shortlisted participants from the following organisations:

1. I considered all IT and IT-enabled service companies listed with the Dhaka Stock Exchange and the Chittagong Stock Exchange
2. I considered non-listed IT and IT service companies with at least 50 employees
3. All tertiary hospitals in Dhaka city
4. Ministry of Health and Family Welfare, Bangladesh
5. Directorate General of Health Services, Bangladesh
6. Bangladesh Public Procurement Authority [Erstwhile Central Procurement and Technical Unit]
7. Central Store of Drugs, Bangladesh

### 4.5 Data Collection

Developing a questionnaire is the first step for the collection of data in any survey-based research project. The following section explains the development and design of the questionnaire.

#### 4.5.1 Questionnaire development

Developing a comprehensive yet understandable questionnaire is a significant part of any survey-based research study (Creswell et al., 2003; Lozada et al., 2019; Mikalef et al., 2019a). The conceptual model developed in Chapter 3 demonstrates all the variables that were the foundation of the questionnaire of this thesis. I created this survey questionnaire based on previously validated instruments. Considering the significant importance of preparing an effective questionnaire, I tried my best to avoid self-reporting bias in the questionnaire design. Variables specified in any hypothesis are usually latent and intangible; therefore, it is difficult or even impossible to quantify or observe directly (Rajasekar et al., 2013; Saunders et al., 2019). Therefore, the framing of appropriate indicators for latent constructs is required to indirectly measure the original unquantifiable concept (Preacher & Hayes, 2004).

Questionnaires are effective data collection instruments for empirical, analytical investigations; still, individual responder's ability to perceive and interpret the questionnaire greatly impacts. Some factors contribute to a great extent in removing such individual influence on the reliability and validity of the questionnaire. Among these factors, ‘appropriate wording’ (Nelson & Skinner, 2013), ‘order of questions’, ‘use of simplified language’, and ‘avoiding technical jargon or providing appropriate explanation where necessary’ should be taken into account (Marc, 2020; Vogt, 2010). The use of a modern visual design for the questionnaire,

with an appropriate size and font, helps the respondent complete the questionnaire more conveniently.

For this thesis, I prepared a questionnaire to capture the latent variables of the research model, namely BDAC, OPT and SSC. The basis of the operationalisation of the construct was based on prior research discussed in section 4.5.2. The possibility of having common method bias within a questionnaire is very common in any survey design. There are four potential sources of common method bias: common source, item characteristics, item context and measurement context (Podsakoff et al., 2003). I applied the necessary procedural remedies suggested by (Podsakoff et al., 2003) to avoid common method bias from all sources. Data analysis [section 5.2 of Chapter 5] confirms that no common method bias exists in the collected dataset.

The likelihood of participation was considered before drafting the questionnaire. A straightforward questionnaire was prepared (M. Liu et al., 2022; Neuman, 2006) and reviewed by industry experts and academicians (Kreuger & Neuman, 2006; Neuman, 2006). Their comments and feedback were used to improve the questionnaire. Before starting the main survey, a small-scale survey with ten respondents was conducted (Bell et al., 2018; Cooper & Schindler, 2014). Participants' feedback from the small-scale survey helped improve the questionnaire's overall design and organisation. Among these ten experts, six had prior questionnaire design experience. Two of them are adept at analytics and research methods. At least five of them have working experience with big data analytics. The ‘face and content validity’ of the questionnaire and the scale used are assessed by experts, making the questionnaire more valid and acceptable (Podsakoff et al., 2003). I prepared a revised questionnaire based on the overall feedback and circulated it to a small group of the target population for the pilot survey. In the survey invitation email and with the questionnaire, I provided WHS and well-being information and procedures to follow in case of any adverse situation.

As mentioned in the earlier sections, I used the Likert scale to measure the extent of agreement or disagreement on a particular set of statements (Cooper & Schindler, 2014; M. Liu et al., 2022; Saunders et al., 2019). Items were sorted based on the symmetry principle and demonstrated in plain English. The Likert scale accumulated respondents' views on subjective statements into quantitative values. Qualtrics, a popular online survey tool, was used to prepare the survey. This tool has many features that help to avoid method bias. For instance, the survey

will automatically detect harsh and patterned answers. The tool accordingly presents the next questionnaire question if any such incident is detected.

### 4.5.2 Questionnaire design

The questionnaire design is crucial for increasing the likelihood of participation (Kreuger & Neuman, 2006). I designed the questionnaire concisely and in a simple manner to help stakeholders with different backgrounds understand it easily. It is advised that ample time should be spent first in clarifying the objectives of the survey to the recipients at the start of a questionnaire (Cooper & Schindler, 2014). The questionnaire design must ensure that data items are appropriate to research objectives and can be collected accurately (Vogt, 2010). The design of the final questionnaire must also consider early on how the coding of the responses can easily be administered and process the collected data (Saunders et al., 2019). Otherwise, an unaligned coding approach with the questionnaire design can lead to a poor data set (Onwuegbuzie & Collins, 2015). I utilised a simplified PLS coding mechanism to capture the full dataset after collection easily.

The biggest source of direct and indirect non-sampling errors is poorly designed questionnaires (Saunders et al., 2019). Therefore, a well-designed questionnaire not only influences the response rate but also increases the quality of responses and, thus, overall conclusions drawn from the survey outcomes. After several iterations incorporating the experts' opinions, I finalised the questionnaire and received a higher response rate than the previous research suggested.

There are different instructions and suggestions available to design an effective questionnaire. Some of them are most settled and widely supported. A questionnaire should keep the following criteria to extract the intended information from the respondents (Bell et al., 2018; Cooper & Schindler, 2014; Creswell et al., 2003; Kreuger & Neuman, 2006; Neuman, 2006; Saunders et al., 2019; Vogt, 2010):

1. Provide clear and concise instructions on how to use and fill out the questionnaire.
2. Articulately define what type of data to collect and store.
3. Allow reasonable time to complete the survey,
4. Administer the survey in a language understood by the respondent,
5. Avoid possible bias in the wording of questions,
6. Maintain the respondent's involvement,

7. In case the questionnaire is fairly long, divide it into smaller segments and provide appropriate instructions for every part.
8. Provide appropriate gratitude to the respondent at the end of the questionnaire so that the respondent feels honoured.
9. Establish the priority of each data item, and
10. Justify each content and provide enough explanation to respondents why this data is important.

I followed various criteria suggested by previous research, including these 10, in finalising the questionnaire for the trial survey. After several modifications before and after a trial survey, the questionnaire was finalised for the final survey. The final questionnaire is presented in Appendix B. It is structured into the following four sections.

**Section One: Basic information**

There was a total of 10 questions in this section. This section mainly aims to retrieve information about persons and their organisations. Personal information such as role, sex, and educational level is collected through this introductory section. Information collected through the section helps to a great extent in getting a better understanding of the sample size. Some fundamental information regarding the organisation, such as location, size, etc., was also collected. Organisational characteristics are important to determine the approximate size of the data volume an organisation generates.

**Section two: Big data analytics capabilities**

This study conceptualised BDACs as a combination of eight human and non-human BDA capabilities. The construct has been taken from an existing empirically validated study (Raut, Mangla, et al., 2021) and later used by several other researchers. In the questionnaire, I positioned BDACs in section two, with eight questions presented to the respondents one after another. Respondents provided feedback on their organisational BDACs on a five-point Likert scale. Every questionnaire section succinctly presents a brief description of questions and fundamental concepts. I received feedback from the respondents that this short description helped them to understand the context and purpose of asking the questions better.

**Section three: public procurement optimisation**

The third section of the questionnaire asked the respondents 14 questions on their organisation's procurement. The construct has been adopted by combining existing empirical studies, such as

(Hendiani et al., 2020; Rezaei et al., 2016), to name a few. The questions in this section mainly endeavour to get a clear picture of the cost of goods/services, quality (in terms of quantity of defects, service call, etc.), services ( service response time), and vendor technical capability.

Any firm's success depends largely on how it manages its procurement and logistics flow on a closed-loop principle (Bag, Wood, Mangla, & Luthra, 2020). Thus, the importance of procurement optimisation in overall supply chain optimisation is paramount to achieving a competitive advantage over competitors. The procurement process involves a series of functions, such as selecting the right supplier and evaluating suppliers' performance, to name a few. Considering the two main uncertain faces of business, i.e. supply and demand, aligning the best procurement strategies to yield optimum benefits from business resources employed is essential (Caniato et al., 2020). Therefore, it was ensured that the questions asked in the questionnaire covered most of the crucial components of the procurement optimisation process.

**Section four: sustainability performance of the healthcare supply chain**

The final section of the questionnaire is based on the questions regarding sustainability performance. It consists of 14 questions based on prior empirically tested constructs by (Tipu & Fantazy, 2019). In this study, I conceptualised sustainability as a two-dimensional construct. The construct is divided into three sub-constructs; therefore, the questionnaire has three sub-sections. Sustainability performance is operationalised as a combination of economic, social and environmental performance. There are some grey areas for measuring sustainability performance. For instance, it is challenging to find financial and environmental information from different companies, as that information attracts legal consequences; therefore, an organisation can only disclose those if necessary.

On the other hand, it is not easy to quantify the social impact of sustainability (Beske-Janssen et al., 2015). Therefore, sustainability performance is measured from a perceptual viewpoint rather than an objective approach. Research confirms that perceptual measurement can be equally effective as objective measurement if conducted effectively and purposefully (Singh et al., 2016). I requested the respondents to provide their opinions on their organisation's sustainability performance on a five-point Likert scale similar to the previous subsections. The most cited sustainability factors are covered in the questionnaire to make it empirically aligned with existing research.

### 4.6 Research Instrumentation/Measures

**Sample and sample size**

The target respondents of this research survey are technology and procurement stakeholders in Bangladesh. Regardless of the response rate, selecting the appropriate sample size is critical in ensuring research credibility and validity (Wolverton, 2009). The appropriate sample size is also important for inferring a statistical and analytic generalisation, and to what extent it can be inferred (Onwuegbuzie & Collins, 2015). There are general guidelines available to decide on an appropriate sample size. For example, in the Structural Equation Modelling (SEM) model, the minimum sample size is ten times the highest number of structural paths of any particular construct (Gefen & Straub, 2005; Hair et al., 2019; Joseph F. Hair et al., 2006).

SEM is a multivariate statistical technique used to analyse complex relationships between observed and latent variables. It enables researchers to test theoretical models by estimating the relationships between variables, providing a way to assess direct and indirect effects in data, and is commonly used in social sciences, business, and healthcare research.

In this study, the highest number of paths directed at any construct is two (Figure 3.4). Therefore, the minimum sample size is twenty. Our sample size is 225, which is way larger than the size suggested by the 10-times rule.

Another popular sample size guideline, named the R2 rule, was proposed by (Joseph F. Hair et al., 2006), suggests considering the following factors that may affect sample size for any SEM statistical analysis. These criteria are as follows:

1. The minimum coefficient of the determinant (R2): determined by the R2 value of SEM,
2. The complexity of the model itself: determined by the highest number of arrows indicated to any particular construct,
3. The significance level of the hypotheses, and
4. Statistical power: 80% is considered standard.

There is another guideline proposed by (Saunders et al., 2019) in determining the sample size. The following factors should be considered when determining sample size.

1. The multivariate distribution of the data,
2. The estimation method,
3. The measure of missing data,
4. The average error variance amount among reflective indicators,
5. Data analysis technique,
6. The population sizes,
7. The number of research questions, and

8. The confidence level at which it is guaranteed that the samples are representative of the entire population.

The sample size also correlates with data analysis techniques and available resources (time, budget, etc) (Bell & Bryman, 2007; Bell et al., 2018; Saunders et al., 2019). Not all of these criteria are quantifiable. The two most important criteria widely used in determining the sample size are the statistical power and the significance level. To achieve 80% of statistical power and find an acceptable R2 value of greater than 0.5 (with a 1% significance level), at least 43 responses are required. Therefore, our sample size for this study is sufficient. It is found that for 10-15 indicators, approximately 200-400 sample size is standard for any SEM method (Joseph F. Hair et al., 2006). The current investigation utilised a sample of 225 from the survey. For path modelling, a sample size of 100-200 is usually appropriate to start with path modelling (Hoyle, 1995). On the other hand, our chosen PLS-SEM provided a valid model with a sample size (Joseph F. Hair et al., 2006). Considering the above discussions, we can conclude that our sample size of 225 is justified and representative of drawing a valid model.

Moreover, the process of sample selection in this study was guided not only by statistical rules but also by contextual relevance. The sample was drawn purposively to include a diverse group of stakeholders directly or indirectly involved in public procurement and technology implementation in Bangladesh. This included professionals from public sector procurement agencies, IT departments, private sector vendors, policy think tanks, and academic institutions. This stratification was essential to capture the multi-stakeholder dynamics that influence BDA adoption and public procurement optimisation (PPO) within a developing economy context. By ensuring representation across different organisational roles and sectors, the study aimed to enhance the external validity of its findings and reduce the risk of selection bias. In addition, the high response rate and quality of completed surveys support the reliability and robustness of the final dataset used for PLS-SEM analysis.

### 4.7 Ethics Considerations

According to the University of Technology Sydney Human Research Ethics Committee [UTS HREC] guidelines, this study has been approved. The approval ID is UTS HREC ETH19-4176. A participant or stakeholder can contact the principal supervisor or the university ethics office to inquire about the ethics issue. This research provided the survey participants with detailed instructions on the way complaints could be raised regarding any aspect of the conduct of this research.

# 5. Data Analysis

This chapter presents the quantitative analysis of this research. It starts with the presentation of demographic information of the participants of this research, followed by a statistical analysis of the obtained responses. Additional statistical tests have been performed to identify potential non-response or 'common method bias' to articulate respondents' intended meanings better. Tests relating to data validity and reliability have also been conducted to ensure that only theoretically relevant constructs are included in the final model. The final model is developed based on valid and potential bias-controlled constructs. Finally, the structured model's significance concerning 'constructs loading' and 'path coefficient' was determined through bootstrapping. The quantitative analysis is concluded by testing hypotheses and determining direct, indirect, or mediating effects among constructs.

## 5.1 Participant Demographic Information

The online survey did produce a compilation of 225 responses. This survey asked 10 demographic questions, including relating to gender, age, work category, level of education, years of experience in the technology sector and data analytics, current role, and business location.

Figure 5.1 summarises participants' gender-related information. Most of the participants identified themselves as male (84%; n=188), while 15% (n=34) of the participants were female. It reflects that male executives highly dominate the technology sector in developing countries such as Bangladesh.

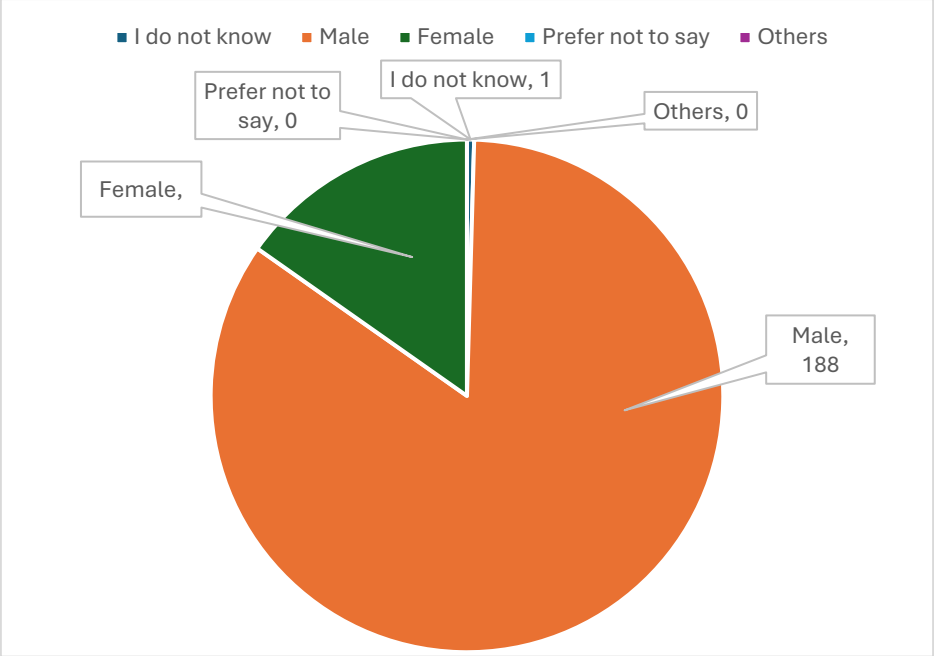



Figure 5.1 Participants' gender

This survey asked participants to indicate their age in the following four range-based categories: 18-25, 26-35, 36-45, and above 45. As shown in Figure 5.2, most participants are aged 36-45 (54%; n=132), which was followed by 26-35 (26%; n=59). Fewer counts of respondents are aged 45 and above (13%; n=28).

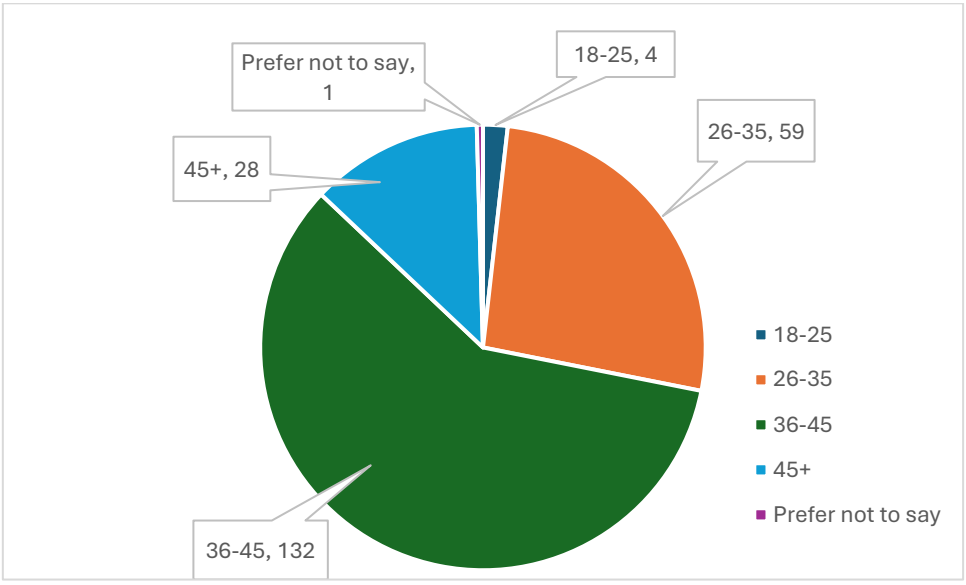
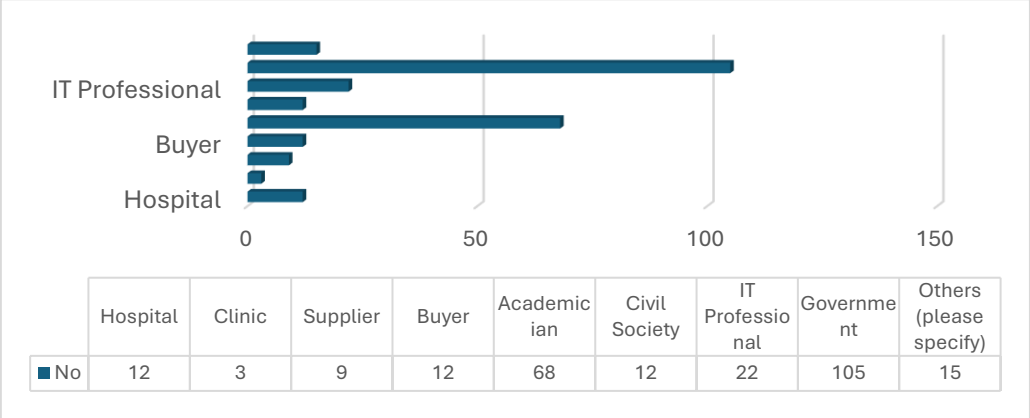



Figure 5.2 Participants' age groups

Participants were asked to indicate the categories of organisations where they had experience of working in. Out of the categories that were listed in the provided questionnaire, the largest

group of participants are found to have worked in government (41%; n=105). This group was followed by academicians (26%; n=68) and IT professionals (9%; n=22). Three percent (n=9) and 1% (n=3) of respondents worked as supplier and in clinics, while the remaining categories included hospital, buying house, and civil society. Figure 5.3 summarises these findings.




| | Hospital | Clinic | Supplier | Buyer | Academician | Civil Society | IT Professional | Government | Others (please specify) |
|---|---|---|---|---|---|---|---|---|---|
| No | 12 | 3 | 9 | 12 | 68 | 12 | 22 | 105 | 15 |

Figure 5.3 Categories of organisations

Participants, however, also indicated that they worked in categories beyond those that appear in this questionnaire. The reported categories, as obtained from participants' responses, included executive, telecommunication, engineering, government jobs, civil servant, operations management, government officer, engineering, electrical engineer, civil servant, industrial automation, service, private, banker, electrical engineer, electrical engineer, and autonomous. In respect of levels of educations completed by respondents, the majority of respondents did complete a Master's-level qualification (n=147), followed by doctoral qualification (n=45), and the completion of a bachelor's degree (n=29). In respect of qualifications below a bachelor's degree, only one respondent did report of having obtained a diploma.

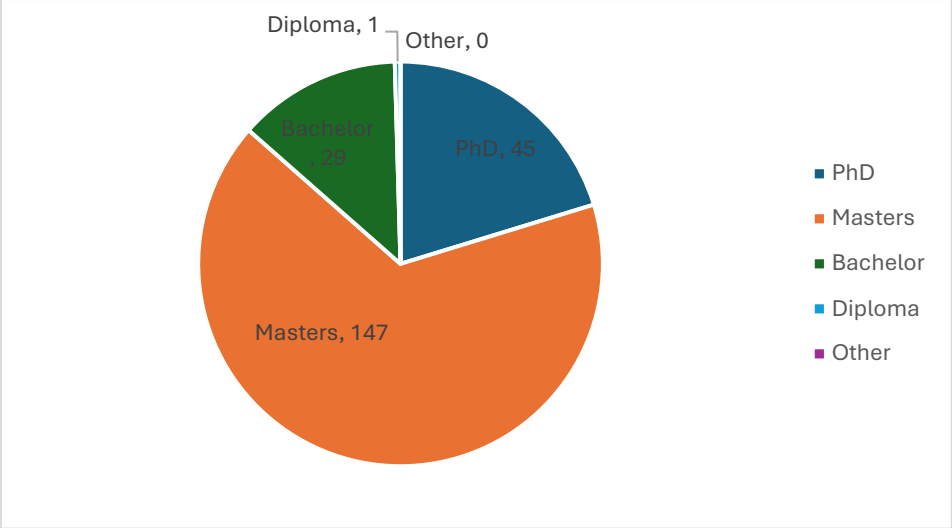



Figure 5.4 Participants' levels of education

In addition to levels of education, participants were also asked to specify their fields of study. The largest group belonged to engineering (32%; n=70), followed by management (19%; n=43). Figure 5.5 summarises participants' fields of study.

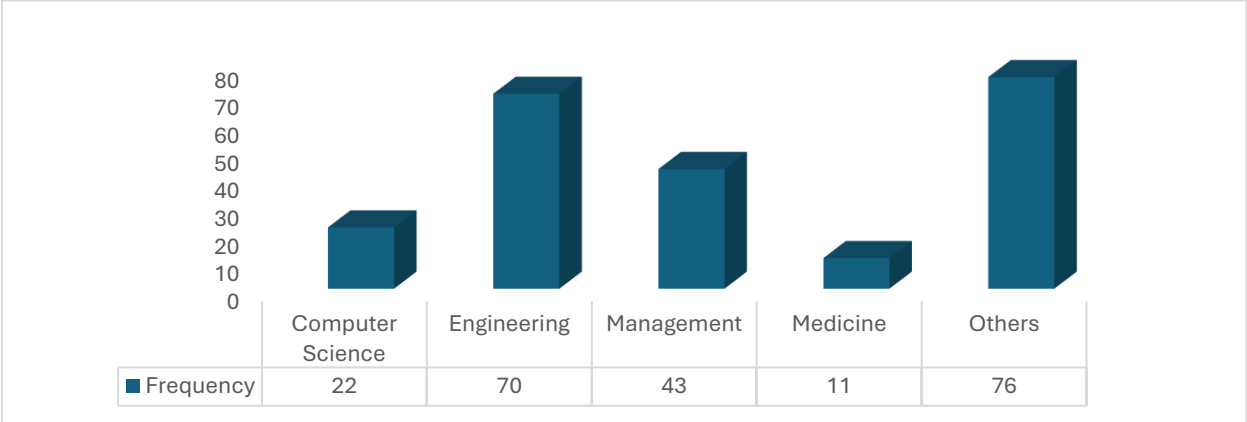



Figure 5.5 Participants' fields of study

Noticeably, a large group of respondents (34%) indicated that they majored in fields other than those indicated in the questionnaire. These fields included economics (n=9), finance (n=4), public policy and administration (n=3), physics (n=3), chemistry (n=3), marketing (n=3) project management (n=2), social work and social sciences (n=2), development studies (n=2), English literature (n=2) and statistics (n=2), along with the appearance of sustainability transitions, disaster management, biological sciences, agriculture, mathematics, pharmacy, sports management, mass communication, and philosophy.

Participants were also asked to indicate their years of experience in the technology sector, where various data analytics tools are in use. The largest group indicated of having more than 10 years of experience (44%; n=95), while many others indicated about having at least seven years of experience (17%; n=37). It was also observed that many respondents had merely one to three years of experience of working in this sector (17%; n=37).

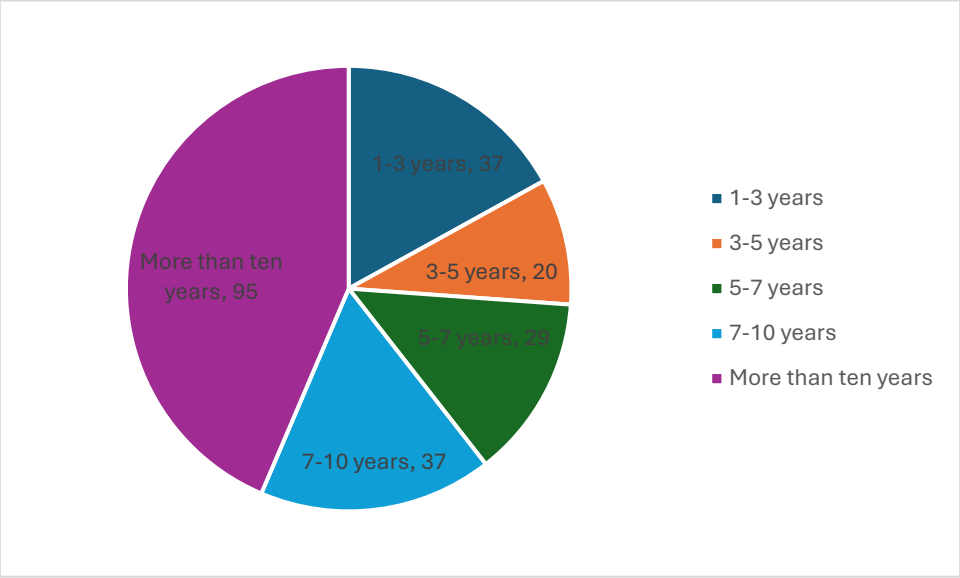



Figure 5.6 Years of experience in the technology sector

Apart from the respondents' experience working in the technology sector, they were also asked about their experience in the use of any type of data analytics, such as SPSS, Excel, Tableau, and others. It was revealed that the largest group of respondents had more than 10 years of experience in data analytics (31%; n=68), followed by one to three years of experience (29%; n=62), seven to ten years of experience (15%; n=33), five to seven years of experience (14%; n=30), and three to five years of experience (11%; n=24).

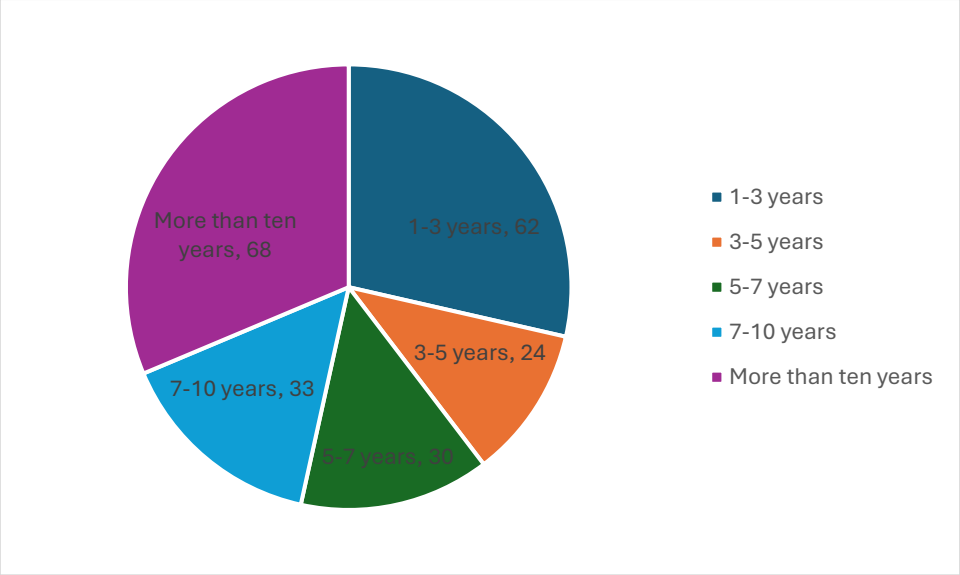
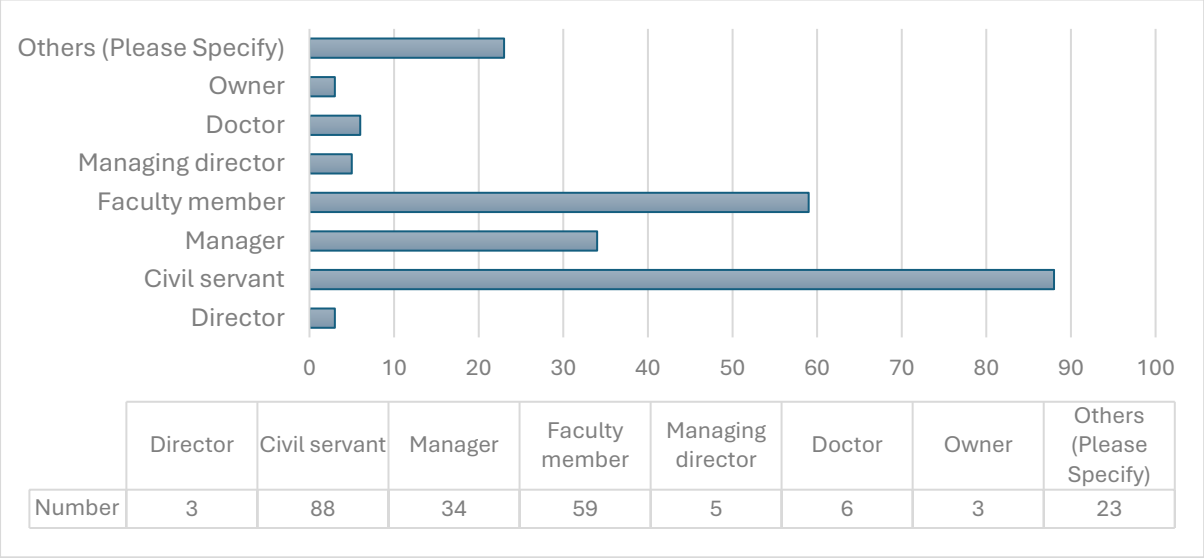



Figure 5.7 Experience in the use of data analytics

In respect of their current roles, the majority of respondents indicated being at work as civil servants (40%; n=88), followed by faculty members (27%; n=59), managers (15%; n=34), doctors (3%; n=6), managing directors (2%; n=5), and business owners (1%; n=3). The remaining 10% of respondents indicated of being at work as engineers, senior engineers, electrical engineers, design leads, analysts, ICT experts, network architects, administrative heads, and software engineers.

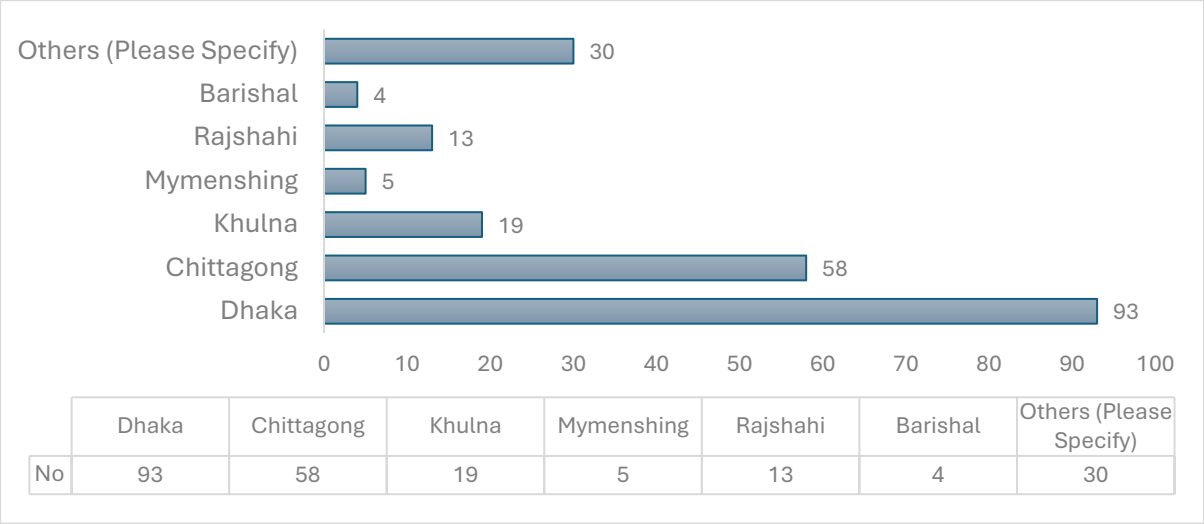



| | Director | Civil servant | Manager | Faculty member | Managing director | Doctor | Owner | Others (Please Specify) |
|---|---|---|---|---|---|---|---|---|
| Number | 3 | 88 | 34 | 59 | 5 | 6 | 3 | 23 |

Figure 5.8 Participants' current roles

Lastly, participants were asked to indicate their work locations. As revealed in Figure 5.9, the largest group of respondents indicated Dhaka (42%; n=93), followed by Chittagong (26%;

n=58), Khulna (9%; n=19), Rajshahi (6%; n=13), Mymenshing (2%; n=5), and Barishal (2%; n=4). Out of the remaining 30% of respondents, Comilla (n=2), Sylhet (n=2), Rangpur (n=2), and overseas-based locations such as Sydney and Melbourne in Australia (n=4) appeared in respect of locations indicated by more than one respondent. The remaining locations were indicated by one respondent each, which included: Cox'sBazar, Faridpur, Narail, Kushtia, Brunei, Berlin, Thailand, London, Toronto, and the Central African Republic. However, irrespective of the prevalence of locations as indicated by respondents, it was ensured that respondents are directly involved with the context of Bangladesh in their current roles.




| | Dhaka | Chittagong | Khulna | Mymenshing | Rajshahi | Barishal | Others (Please Specify) |
|---|---|---|---|---|---|---|---|
| No | 93 | 58 | 19 | 5 | 13 | 4 | 30 |

Figure 5.9 Participants' location of work

## 5.2 Data Assessments: Distribution and Potential bias

The following four 'data characteristics' have been addressed in this research: a) nonresponse bias, b) common method bias, also known as 'common method variance', c) distribution, and d) collinearity. While collinearity is addressed later in this chapter—see Table 5.15—nonresponse bias, common method bias, and normality assessments are presented below.

### *Nonresponse bias*

Nonresponse is "a survey response that falls outside the range of responses that survey designers consider valid" (Berg, 2005, p. 865). Nonresponse bias occurs when subjects who decline to participate in a study or drop out during 'data collection' are systematically different from those who participate (Prince, 2012). In short, it relates to the possibility that some respondents could become underrepresented in a given study (Berg, 2005). Nonresponse bias is usually caused by the presence of weakness in the adopted sampling method, the overall

research design in action, or the unwillingness of the selected sample to participate (Alvarez & VanBeselaere, 2005; Berg, 2005). While some researchers overlook it, others emphasise its potential to distort findings produced through the analysis of the collected data. Nevertheless, response rates often differ on the basis of, or influenced by, the demographic mosaic of a sample.

Usually, nonresponse bias could become critical when the response rate becomes lower than 70% (Prince, 2012). The potential of the presence of nonresponse bias in a study is assessed by comparing between the response and nonresponse rates, besides assessing the demographics of respondents and nonrespondents (Prince, 2012). In this study, 2170 individuals were invited to participate in an online survey, which generated 225 responses, equating to a response rate of 10.36%. The nonrespondents were then followed up with multiple reminder emails in an attempt to encourage them to participate. While the initial invitation generated 79 usable responses, the first, second and third email reminders generated 48, 67 and 31 usable responses, respectively. Despite the apparent low response rate from the part of the invited sample, there were no observable differences between respondents and nonrespondents with respect to their demographic characteristics.

***Common method bias (CMB)***

CMB is the "variance that is attributable to the measurement method rather than to the constructs the measures represent" (Podsakoff et al., 2003, p. 879). The problems with the measurement method can be attributed to the content of the measurement items that are in use, the type of scales that are applied, the format in use for the production of responses, and the context of the concerned study (Podsakoff et al., 2003). Besides, CMB could also be present owing to response biases such as social desirability. While Kock et al. (Kock et al., 2021) described CMB to appear when the same response method—e.g., a survey—is utilised to capture both independent and dependent variables, according to Podsakoff et al. (2003), CMB is one of the main sources of measurement-related errors, which could potentially threaten the validity of conclusions in terms of the relationship between dependent and independent variables.

Podsakoff et al. (2003) produced a framework comprised of seven recommendations for the control of CMB, where one's research settings guide the choice of approach. They emphasised on the following five approaches: questionnaire design remedies, single-specific-method factor

approach, multiple-specific method-factors approach, single-common-method-factor, and multiple-common-method-factors approach. It was also suggested that one might consider questionnaire design measures and the single-common-method-factor approach when independent and dependent variables cannot be measured in different contexts, and the sources of method bias are difficult to identify.

In this research, Harman's single-factor test was adopted to assess CMB through the use of IBM SPSS Statistics. The adoption of this approach was enabled through the incorporation of all indicators from all three constructs in use in this study — i.e., BDAC, PPO, and SSC_PERF — into the frame of a single-factor analysis to assess whether a single factor can account for the majority of variance being occurred (i.e., the degree of spread in dataset). While a single factor is expected not to explain more than 50% of the variance in data, in the case of this study, a single factor explained only 31% of the variance, as indicated in Table 5.1. These results indicated the potential of **the absence of CMB** in the data used in this study.

Table 5.1 SPSS output for Harman's single factor test [total variance explained]
Extraction method: Principal axis factoring

| | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| Factor | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 11.746 | 32.629 | 32.629 | 11.154 | 30.982 | 30.982 |
| 2 | 3.118 | 8.660 | 41.289 | | | |
| 3 | 2.573 | 7.148 | 48.437 | | | |
| 4 | 1.725 | 4.792 | 53.228 | | | |
| 5 | 1.589 | 4.415 | 57.643 | | | |
| 6 | 1.518 | 4.217 | 61.860 | | | |
| 7 | 1.274 | 3.538 | 65.398 | | | |
| 8 | 1.080 | 3.001 | 68.399 | | | |
| 9 | .920 | 2.554 | 70.954 | | | |
| 10 | .816 | 2.266 | 73.219 | | | |
| 11 | .760 | 2.110 | 75.329 | | | |
| 12 | .711 | 1.976 | 77.305 | | | |
| 13 | .629 | 1.747 | 79.053 | | | |
| 14 | .582 | 1.616 | 80.669 | | | |
| 15 | .540 | 1.500 | 82.169 | | | |
| 16 | .504 | 1.401 | 83.570 | | | |
| 17 | .490 | 1.361 | 84.931 | | | |
| 18 | .461 | 1.280 | 86.211 | | | |
| 19 | .423 | 1.174 | 87.385 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 20 | .417 | 1.157 | 88.542 | | | |
| 21 | .383 | 1.063 | 89.605 | | | |
| 22 | .373 | 1.035 | 90.641 | | | |
| 23 | .355 | .987 | 91.628 | | | |
| 24 | .340 | .945 | 92.573 | | | |
| 25 | .313 | .869 | 93.442 | | | |
| 26 | .296 | .822 | 94.264 | | | |
| 27 | .289 | .804 | 95.068 | | | |
| 28 | .277 | .771 | 95.839 | | | |
| 29 | .246 | .684 | 96.522 | | | |
| 30 | .234 | .650 | 97.172 | | | |
| 31 | .204 | .568 | 97.740 | | | |
| 32 | .202 | .560 | 98.301 | | | |
| 33 | .168 | .467 | 98.768 | | | |
| 34 | .165 | .458 | 99.226 | | | |
| 35 | .144 | .400 | 99.625 | | | |
| 36 | .135 | .375 | 100.000 | | | |

***Distribution and normality assessment***

Data distribution characterises the location and variability of a dataset, which are critical in structural equation modelling (SEM) owing to their association with Type-I errors i.e., a false positive conclusion through a rejection of the null hypothesis (Byrne, 2010; Cain et al., 2017). One, in this respect, could usually consider three normality assessments, including univariate skewness, univariate kurtosis, and multivariate kurtosis (Finney & DiStefano, 2006). Kurtosis, here, measures the peakedness of a distribution, i.e., the distribution of values around the mean, while skewness measures symmetry, i.e., the deviation of values from symmetry around the mean (Cain et al., 2017; Hair Jr et al., 2017).

According to Byrne (2010), multivariate kurtosis presents major concerns for SEM estimates. While high kurtosis is an indication of outliers, a multivariate kurtosis with a value above 3 indicates non-normality and the potential for the presence of inaccurate estimates, especially when the maximum likelihood estimation is applied (Finney & DiStefano, 2006). In similitude to kurtosis, the value of skewness for normal distribution is zero, while studies suggest that a skewness value higher than two could be a reason for concern in SEM analyses. However, many studies presented different value ranges to ideally act as guidelines for the confirmation of normality. For instance, Chou and Bentler (1995) indicated that the values of ±2 and ±7 for skewness and kurtosis, respectively, indicate a nonnormal distribution.

Importantly, distributional assumptions vary between the SEM techniques in use; for instance, covariance-based SEM assumes a normal distribution dataset, while partial least squares SEM (the one applied in this study) doesn't assume the presence of a normal distribution. In this respect, Hair Jr et al. (2017) stated that:

> "a general guideline for skewness is that if a number is greater than +1 or lower than –1, this is an indication of substantially skewed distribution. For kurtosis, the general guideline is that if the number is greater than +1, the distribution is too peaked. Likewise, a kurtosis of less than – 1 indicates a distribution that is too flat. Distributions exhibiting skewness and/or kurtosis that exceeds these guidelines are considered nonnormal" (p. 61).

Hair Jr et al. (2017) guideline is particularly stated in the context of partial least squares SEM, a technique that has been applied in this study, as discussed in the subsequent section. The values of skewness and kurtosis that appear in Table 5.2 are derived from the application of the SmartPLS 3 package.

Table 5.2 Normality tests: skewness and kurtosis

| Construct | Items | Missing | Mean | Median | SD | Excess Kurtosis | Skewness |
|---|---|---|---|---|---|---|---|
| **BDAC** | BDAC1 | 0 | 3.4 | 4 | 1.1 | -1.1 | -0.1 |
| | BDAC2 | 0 | 4.3 | 5 | 0.8 | 1.5 | -1.3 |
| | BDAC3 | 0 | 3.4 | 4 | 1.0 | -0.4 | -0.4 |
| | BDAC4 | 0 | 4.3 | 4 | 0.8 | 1.4 | -1.1 |
| | BDAC5 | 0 | 4.2 | 4 | 0.8 | 1.0 | -1.1 |
| | BDAC6 | 0 | 3.7 | 4 | 1.0 | -0.4 | -0.5 |
| | BDAC7 | 0 | 3.9 | 4 | 0.8 | 0.6 | -0.7 |
| | BDAC8 | 0 | 3.3 | 4 | 1.1 | -0.6 | -0.3 |
| **PPO** | PO2 | 0 | 3.6 | 4 | 1.0 | -0.8 | -0.2 |
| | PO3 | 0 | 3.7 | 4 | 0.9 | -0.6 | -0.2 |
| | PO6 | 0 | 3.7 | 4 | 0.8 | -0.3 | -0.1 |
| | PO7 | 0 | 3.3 | 3 | 1.0 | -0.6 | -0.1 |
| | PO8 | 0 | 3.3 | 3 | 1.1 | -1.1 | 0.0 |
| | PO9 | 0 | 3.4 | 3 | 0.9 | -0.6 | 0.0 |
| | PO4 | 0 | 3.2 | 3 | 1.0 | -0.8 | -0.2 |
| | PO5 | 0 | 2.9 | 3 | 1.0 | -0.6 | 0.2 |
| | PO1 | 0 | 3.2 | 3 | 0.9 | -0.5 | 0.0 |
| | PO10 | 0 | 3.1 | 3 | 1.1 | -1.0 | 0.2 |
| | PO11 | 0 | 3.2 | 3 | 1.0 | -0.9 | 0.1 |
| | PO12 | 0 | 3.1 | 3 | 1.1 | -1.0 | 0.3 |
| | PO13 | 0 | 3.2 | 3 | 1.0 | -0.6 | 0.4 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | PO14 | 0 | 3.4 | 3 | 0.9 | -0.8 | 0.0 |
| **SSC PERF** | SSC1 | 0 | 3.2 | 3 | 1.1 | -1.0 | 0.1 |
| | SSC2 | 0 | 3.1 | 3 | 1.1 | -1.0 | 0.1 |
| | SSC3 | 0 | 3.1 | 3 | 1.0 | -0.6 | 0.1 |
| | SSC4 | 0 | 3.5 | 4 | 0.9 | -0.4 | -0.3 |
| | SSC5 | 0 | 3.2 | 3 | 1.0 | -0.7 | -0.1 |
| | SSC6 | 0 | 3.2 | 3 | 1.1 | -0.8 | -0.1 |
| | SSC7 | 0 | 3.2 | 3 | 1.0 | -0.8 | -0.1 |
| | SSC8 | 0 | 3.2 | 3 | 1.0 | -0.8 | -0.1 |
| | SSC9 | 0 | 3.4 | 4 | 1.0 | -0.4 | -0.4 |
| | SSC10 | 0 | 3.5 | 4 | 0.9 | -0.2 | -0.5 |
| | SSC11 | 0 | 3.6 | 4 | 0.9 | 0.0 | -0.6 |
| | SSC12 | 0 | 3.4 | 4 | 1.0 | -0.6 | -0.4 |
| | SSC13 | 0 | 3.5 | 4 | 1.0 | -0.3 | -0.5 |
| | SSC14 | 0 | 3.6 | 4 | 1.0 | 0.1 | -0.8 |

For BDAC, items BDAC1, BDAC2, BDAC4, and BDAC5 presented indications of nonnormal distributions as their values of skewness and kurtosis are higher than the boundaries of ±1. However, not all items did exhibit large deviations from a normal distribution. Besides BDAC, PPO has a few items that exhibited mild forms of deviations from normality – PO8, PO10, and PO12. SSC PERF indicated a normal distribution as its skewness and kurtosis values fell between +1 and –1. Hence, it could be concluded that the distributional issues that are insofar noted would not affect the estimates that are to be produced in this research as they are mild in form, while the PLS-SEM approach has been adopted in this research, which works well with such distribution.

### 5.3 Hypothesis Testing

Quantitative data was collected to test the hypotheses of this study. While a number of techniques could be applied in hypothesis testing, the appropriate choice is to be informed by the nature of variables and distributional assumptions that are present around the dataset. Hypotheses in IS research are tested through regression or structural equation modelling (SEM) techniques. SEM techniques are considered second-generation data analysis techniques that subject IS research to rigorous, high-quality statistical analysis (Gefen et al., 2000). On the other hand, regression is considered to represent a first-generation statistical tool with less capability to analyse complex relationships between variables. Regression tools such as linear regression and (M)ANOVA analyse one layer of linkages between independent and dependent variables at a time, while SEM tools "model relationships between multiple independent and dependent constructs simultaneously" (Gefen et al., 2000, p. 4).

SEM techniques gained popularity in the fields of behavioural and IS research (Hair et al., 2017). One may argue that SEM should, instead, be preferred owing to offering more capabilities for the test of complex relationships, while also being rigorous in nature. This technique "permits complicated variable relationships to be expressed through hierarchical or non-hierarchical, recursive or non-recursive structural equations" in a single model (Gefen et al., 2000, p. 4), while its popularity has been associated with its multiple analysis capabilities. SEM is mostly denoted being a hybrid path of analysis as it combines several multivariate procedures, including confirmatory factor analysis, path analysis, canonical correlation, and regression analysis (Gefen et al., 2000; Hox & Bechger, 1998; Musil et al., 1998). A more prominent advantage is its capacity to analyse both the measurement and structural model, which allows for (1) measurement errors to be analysed and (2) factor analysis to be combined with hypothesis testing in a single operation (Gefen et al., 2000; Nachtigall et al., 2003). SEM is also preferred owing to its capability to analyse latent variables, i.e., factors underlying observable variables (Nachtigall et al., 2003).

Although the strengths of SEM are self-evident, this technique is often seen being a complicated procedure, and thus, it may present difficulty with respect to the understanding and interpretation of data analysis (Nachtigall et al., 2003). Despite the presence of such difficulties, use of SEM has become a commonplace practice as many researchers opt to use it for the strengths that it offers, although without understanding the actual necessity for attaining a fruitful application (Nachtigall et al., 2003). While the complexity of this technique, its underlying assumptions regarding sample size and data distribution, and its growing popularity also make this method susceptible to misuse (Hox & Bechger, 1998); scholars, in recent years, developed, tested, and provided steps and procedures for the effective application of SEM techniques, see, for instance, Hair Jr et al. (2017).

There are two SEM-based methods for estimating the relationships between constructs in a structural model – i.e., covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). According to Hair et al. (Hair et al., 2017), the choice between the two methods is informed by the research context and the extent of theory development. CB-SEM supports an explanatory pursuit with strong theoretical pillars, while PLS-SEM supports an explorative analysis and allows researchers to predict the target construct (Hair et al., 2017). Given the explorative nature of this study and the shortage of theoretical perspectives on BDAC, public procurement optimisation or sustainability performance, it is determined that PLS-SEM would

be more suitable to test my research model. Moreover, all three areas are relatively new and still underdeveloped in IS research, as I discussed in the literature review chapter.

### 5.3.1 PLS path model estimation

I applied PLS-SEM, a variance-based technique, to test the proposed model and hypotheses. Besides its capability to support an explorative investigation, PLS-SEM was more suitable than CB-SEM because it is less sensitive to sample sizes and nonnormal data distribution (Hair et al., 2017). With two (2) independent variables, we needed a sample size of only 90 cases for a statistical power of 80%, but we used 225 cases. While CB-SEM works well with continuous data with normal distribution, PLS-SEM generates accurate estimates when data fails to meet these conditions. Nonetheless, PLS-SEM presents greater statistical power than CB-SEM, which implies that PLS-SEM is more likely to report a significant relationship when the relationship is significant in the population (Hair et al., 2017). Many studies in IS research have applied PLS-SEM for the same reasons – exploratory research, prediction, theory development, sample size and data distributional assumptions (Al-Emran et al., 2018; Hair et al., 2017).

Approaches to model estimation differ between CB-SEM and PLS-SEM. The latter is a nonparametric statistical method, while the former relies on the theory of maximum likelihood (ML). For this reason, CB-SEM works only well with data that fits a normal distribution curve. Also, CB-SEM assumes a composite model approach, while the PLS-SEM assumes a common factor model approach. A composite model approach assumes linear combinations of indicators defined as composites. In contrast, a common factor model assumes the variance of a set of indicators can be perfectly explained by the existence of a common factor and individual random error" (Ringle et al., 2018). Therefore, PLS-SEM is considered a variance-based approach (Hair Jr et al., 2017).

The PLS-SEM analysis process involves four aspects, i.e., defining our research goal, specifying the structural model, specifying the measurement model, and evaluating the results (Ringle et al., 2018). In light of the research goal, I sought to examine the effect of BDAC on public procurement optimisation and the sustainability performance of the healthcare supply chain. A structural model with three hypotheses was developed, which I tested using the SmartPLS 3 package. Below, I present the measurement model results, followed by the structural model and hypothesis results. First, the preliminary models are presented before item

deletion, followed by the presentation of the refined model with acceptable reliability and validity.

### 5.3.2 Preliminary model estimation

Before analysing the structural model, researchers are expected to detail the measurement model and assess the reliability and validity of measurement items. According to Hair et al. (Hair et al., 2017), measurement theory "specifies how the latent variable is measured" (p. 13). This study involved reflectively specified constructs rather than formatively specified ones. This was because we determined that the primary constructs cause the indicators; for instance, it was determined that supply chain sustainability performance causes economic, social, and environmental sustainability performance.

With reflective measures, assessing our measurement model involves examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2017; Ringle et al., 2018). The assessments mentioned above are emphasised for reflective measurement models used in this study. These reliability and internal consistency measures are critical as, in the case of reflective models, indicators account for the observed variances or covariances (Petter et al., 2007). I determined the reliability and validity of our measurement model based on the thresholds recommended by many authors and as specified by (Hair et al., 2017)

- Indicator reliability was based on outer loadings higher than 0.7
    - Factor loading relevance testing: Factor loading lower than 0.4 were deleted, and factor loadings > 0.4 < 0.7 were retained only when deletion did not increase internal consistency reliability
- Internal consistency reliability was determined based on rho_A, composite reliability (C.R.) and Cronbach's alpha. Specifically, the rho_A and the C.R. are higher than 0.7.

    As Cronbach's Alpha may be influenced by scale length, sample size, and other data characteristics, alternative measures, particularly C.R., were proposed (Hair Jr et al., 2017; Spiliotopoulou, 2009). However, Hair et al. (2021) argue that while Cronbach's alpha may be too conservative, the C.R. may be too liberal. Therefore, "the construct's true reliability is typically viewed as within these two extreme values" (Hair et al., 2021, p. 78). It is suggested that the reliability coefficient rho_A falls between the conservative Cronbach's alpha

and the liberal C.R and, therefore, would provide a better assessment of internal consistency reliability (Hair et al., 2021).

- Convergent validity was determined based on average variance extracted (AVE) higher than 0.5.
- Discriminant validity was determined based on the following.
    - Cross-loadings where the outer loadings on a construct have to be greater than any of its cross-loadings on other constructs
    - Fornell-Larcker criterion, the square root of the AVE values has to be greater than latent variable correlations.
    - Heterotrait-monotrait ratio (HTMT), where the HTMT values have to be lower than 0.9 (Henseler et al., 2015)

Chapters 3 and 4 discussed the theoretical positions of the ways this structural model was derived from existing studies. I ran the model as hypothesised with all constructs and measurement items in the preliminary model estimation. The results of the measurement are reported below. The Model in Figure 5.10 shows the initial model results; however, a few measurement items are needed to achieve the required reliability and reliability threshold. The refined measurement model is discussed later in this chapter.

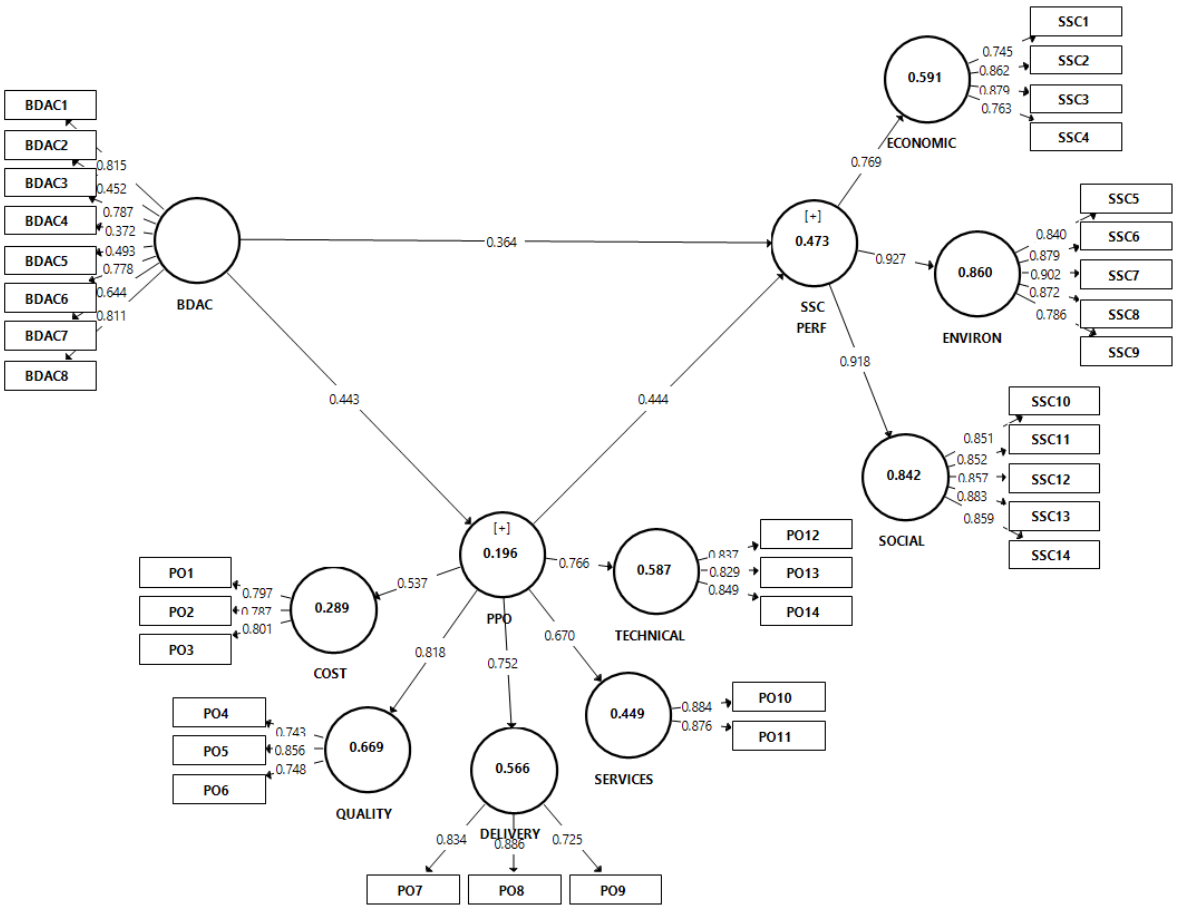



Figure 5.10 Preliminary model estimation before reliability and validity assessment

Big data analytics capabilities (BDAC)

BDAC depicts the organisational capabilities that bring a sustainable competitive advantage for a firm in a big data environment (Wamba et al., 2017). BDAC has been operationalised using eight reflective items adopted from (Raut, Mangla, et al., 2021). These items were coded by BDAC1 – BDAC8, as shown in the Table below. The measures were designed to capture capabilities for handling voluminous data (BDAC1), real-time access to data for decision-making (BDAC2), handling the variety of data formats (BDAC3), improved data accuracy (BDAC4), data-driven intelligence (BDAC5), infrastructure (BDAC6), interchangeability of services (BDAC7), and staff competences (BDAC8). All items were bundled to represent a first-order reflective construct. Table 5.3 below shows the BDAC construct's factor loadings, internal consistency, and convergent validity.

Table 5.3 Preliminary measurement model for BDAC

| Latent Variable | Items | Factor Loading | Cronbach's Alpha | rho_A | C.R. | AVE |
|---|---|---|---|---|---|---|
| **Big Data Analytic Capabilities** | BDAC1 | 0.815 | 0.833 | 0.872 | 0.856 | 0.443 |
| | BDAC2 | 0.452 | | | | |
| | BDAC3 | 0.787 | | | | |
| | BDAC4 | 0.372 | | | | |
| | BDAC5 | 0.493 | | | | |
| | BDAC6 | 0.778 | | | | |
| | BDAC7 | 0.644 | | | | |
| | BDAC8 | 0.811 | | | | |

Among the items used to measure BDAC, the following items did not raise a factor loading of 0.7 and above. Values presented in parentheses represent factor loadings for these items. BDAC2 (0.452) – Real-time assessment of data and information has helped the organisation in better decision making; BDAC4 (0.372) – Truthfulness and accuracy of data have helped our organisation; BDAC5 (0.493) – Data-driven intelligence has made our decision-making more effective; and BDAC7 (0.644) – The interchangeability of services (cloud, mobile, and analytics) plays a key role in our organisation. These items were selected as items for deletion from the final measurement model; however, as earlier mentioned, such items were deleted when deletion increases internal consistency between indicators. Yet, till this point, this model did not achieve desirable convergent validity, given an AVE of 0.443, slightly lower than the recommended value of 0.5. However, it achieved acceptable internal consistency reliability since Cronbach's alpha, rho_A, and C.R. achieved the recommended thresholds.

***Public procurement optimisation (PPO)***

From a sustainable standpoint, public procurement optimisation significantly reduces procurement cycle time, optimises resource usage for procurement, and thus optimally utilises the procured goods or services (Bag, Dhamija, et al., 2020). This study operationalised PPO as a second-order reflective construct with five first-order factors: cost, quality, delivery, services and technical capability (Garg, 2021; Hendiani et al., 2020; Ijadi Maghsoodi et al., 2018; Jain & Singh, 2020; Kant & Dalvi, 2017; Kumar et al., 2019; Rezaei et al., 2016). I imply that PPO could influence cost, quality, and service optimisation with a second-order reflective model. Regarding cost optimisation, we measured the extent to which firms optimise costs related to material cost (PO1), transport cost (PO2), and incidental cost (PO3). To measure quality, I assessed the extent to which the firm's suppliers deliver non-defective items (PO4), handle abnormal quality problems (PO5), and attain quality certification (PO6). We measured delivery

optimisation by considering the on-time delivery (PO7), early delivery (PO8) and a week's lead time (PO9). I measured services optimisation with two observed items: supplier support for complaints (PO10) and after-sale services (PO11). Lastly, the technical capability was measured with three indicators, including supplier infrastructure for R&D (PO12), patents registered (PO13), and collaboration with the firm (PO14). The preliminary measurement model for PPO is presented in Figure 5.11 and Table 5.4.

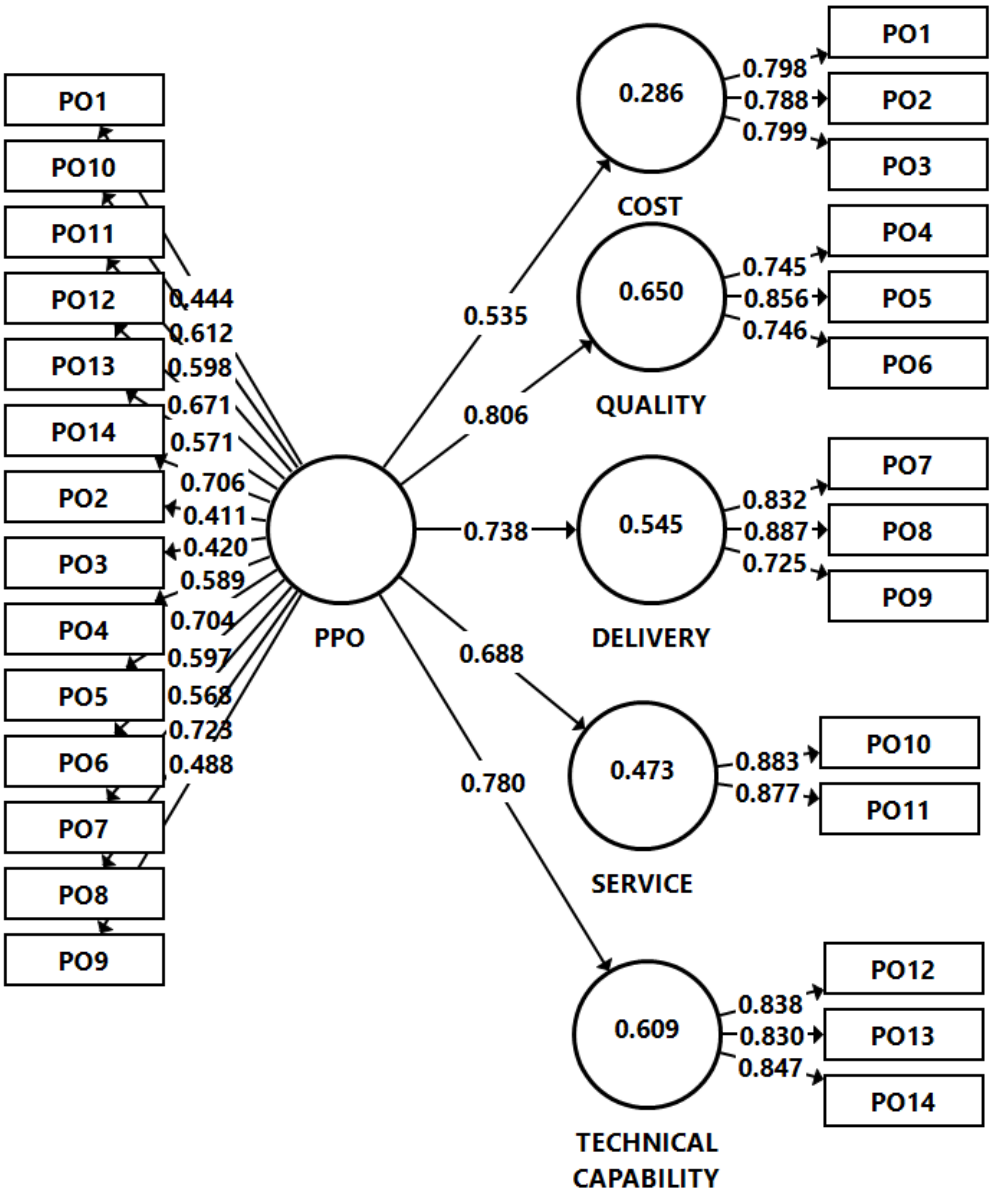



Figure 5.11 Model estimation for public procurement optimisation

The reliability and validity assessments for the above model are summarised in Table 5.4. First, it has presented the outer loadings for the PPO construct (in Table 5.4), the outer

loadings for the first-order constructs reflected by PPO (in Table 5.5), and later, the factor loading for each construct of PPO (in Table 5.6).

Table 5.4 PPO outer loadings

| Latent Variable | Items | Outer Loading | Cronbach's Alpha | rho_A | C.R. |
|---|---|---|---|---|---|
| **Public Procurement Optimisation** | PO1 | 0.444 | 0.849 | 0.861 | 0.877 |
| | PO2 | 0.411 | | | |
| | PO3 | 0.420 | | | |
| | PO4 | 0.589 | | | |
| | PO5 | 0.704 | | | |
| | PO6 | 0.597 | | | |
| | PO7 | 0.568 | | | |
| | PO8 | 0.723 | | | |
| | PO9 | 0.488 | | | |
| | PO10 | 0.612 | | | |
| | PO11 | 0.598 | | | |
| | PO12 | 0.671 | | | |
| | PO13 | 0.571 | | | |
| | PO14 | 0.706 | | | |

As per Table 2, indicators PO1, PO2, PO3, and PO9 present low outer loading, indicating indicator reliability problems. These items were assessed based on the first-order constructs to determine whether they achieved indicator reliability. The item reliability values for each first-order construct are reported in Table 5.5.

Table 5.5 Measurement model for public procurement optimisation

| Second-Order Construct | First-Order Constructs (Reflective) | Items | Factor Loading | Cronbach's Alpha | rho_A | C.R. | AVE |
|---|---|---|---|---|---|---|---|
| **PPO** | Cost | PO1 | 0.798 | 0.709 | 0.710 | 0.838 | 0.632 |
| | | PO2 | 0.788 | | | | |
| | | PO3 | 0.799 | | | | |
| | Quality | PO4 | 0.745 | 0.685 | 0.697 | 0.827 | 0.615 |
| | | PO5 | 0.856 | | | | |
| | | PO6 | 0.746 | | | | |
| | Delivery | PO7 | 0.832 | 0.751 | 0.788 | 0.857 | 0.668 |
| | | PO8 | 0.887 | | | | |
| | | PO9 | 0.725 | | | | |
| | Service | PO10 | 0.883 | 0.709 | 0.709 | 0.873 | 0.775 |
| | | PO11 | 0.877 | | | | |
| | Technical Capability | PO12 | 0.838 | 0.790 | 0.796 | 0.876 | 0.703 |
| | | PO13 | 0.830 | | | | |
| | | PO14 | 0.847 | | | | |

Assessing the reliability and validity of first-order constructs, it is determined that all variables achieved the desired indicator reliability with factor loadings mostly above the recommended

level for reflective models. We confirmed that the observed variables for each construct explain at least 50% of the respective variables. The constructs attained the desired internal consistency reliability with Cronbach's alpha, rho_A, and C.R. values above 0.7. First-order variables achieved convergent validity with AVE between 0.615 and 0.775. To this end, we identified no items for deletion in the observed measures. As indicated by Awang (2012), we assessed the significance of the assumed association between the first-order constructs (cost, delivery, quality, services and technical capability) and the second-order construct (PPO). All first-order constructs returned a significant p-value and t-statistic, as shown in Table 5.6.

Table 5.6 Measurement model for public procurement optimisation

| Second-Order Construct | First-Order Constructs (Reflective) | Factor Loading | T-statistic | P-Value | Significant? |
|---|---|---|---|---|---|
| **PPO** | Cost | 0.535 | 7.5 | 0.000 | Yes |
| | Delivery | 0.806 | 19.7 | 0.000 | Yes |
| | Quality | 0.738 | 28.1 | 0.000 | Yes |
| | Services | 0.688 | 15.4 | 0.000 | Yes |
| | Technical Capability | 0.780 | 23.5 | 0.000 | Yes |

With PPO examined as a second-order reflective construct, all first-order variables achieved indicator reliability with factor loadings ranging from 0.535 to 0.806. While cost optimisation returned a factor loading lower than 0.7, suggesting a lack of indicator reliability, we assessed the p-values for each factor to determine whether it was significant. I conducted a two-tailed Bias Corrected and Accelerated (BCa) Bootstrap with 5000 subsamples. The loadings and p-values are reported in the Table above. All constructs returned a significant p-value as reflective first-order items for PPO. Moreover, the t-statistics are all higher than 1.96.

***Sustainability performance in healthcare supply chain (SSC PERF)***

SSC PERF was operationalised as a second-order construct with three reflective variables: economic, environmental, and social sustainability. The SSC scale was adopted from (Tipu & Fantazy, 2019). Economic sustainability relates to creating economic value from a firm's project or decision. Thus, it means that decisions are to be made in the most equitable and fiscally sound way possible, not ignoring other aspects of sustainability. In our scale, we measured economic sustainability based on a decrease in the cost of material purchased (SSC1), a decrease in the cost of energy consumption (SSC2), a decrease in waste discharge fees (SSC3), and an improvement in ROI (SSC4). Environmental sustainability performance

relates to the commitment to protecting the environment by reducing the negative environmental impact of a firm's activities.

This research measured the environmental sustainability based on a reduction in air emission (SSC5), a reduction in waste (SSC6), a decrease in consumption of harmful materials (SSC7), a decrease in the frequency of environmental accidents (SSC8), and an increase in energy saving due to conservation improvements (SSC9). Lastly, social sustainability performance reflects the social consequences of a firm's social activity. Social sustainability refers to the values that promote equality and respect for individual rights in a welfare society. We measured social sustainability as an improvement in stakeholder welfare (SSC10), improvement in community health and service (SSC11), reduction in environmental impacts and risks to the public (SSC12), improvement in occupational health and safety (SSC13), and improved awareness and protection of claims and rights of people (SSC14). The preliminary measurement model for SSC is presented in Figure 5.12 and Table 5.7.

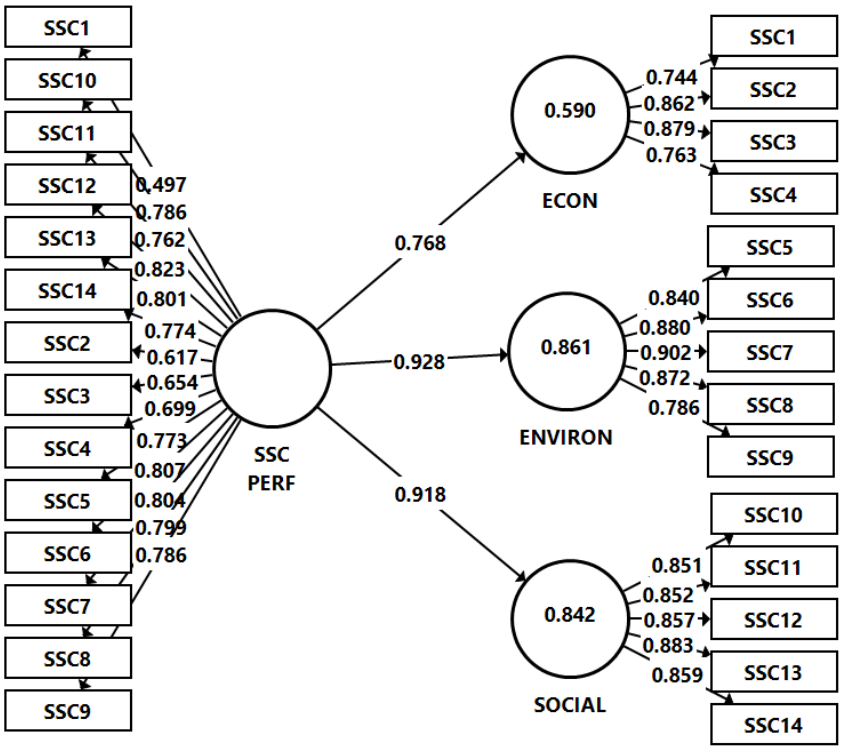



Figure 5.12 Model estimation for sustainability performance

The reliability and validity assessments for the above model are summarised below. We present the outer loadings for the SSC PERF construct (in Table 5.7), the outer loadings for the first-order constructs reflected by SSC PERF (in Table 5.8), and later, the factor loading for each construct and significance level (in Table 5.9).

Table 5.7 Estimation of sustainability performance indicator outer loadings

| Latent Variable | Items | Outer Loading | Cronbach's Alpha | rho_A | C.R. | AVE |
|---|---|---|---|---|---|---|
| **Sustainability Performance** | SSC1 | 0.497 | 0.937 | 0.941 | 0.946 | 0.558 |
| | SSC2 | 0.617 | | | | |
| | SSC3 | 0.654 | | | | |
| | SSC4 | 0.699 | | | | |
| | SSC5 | 0.773 | | | | |
| | SSC6 | 0.807 | | | | |
| | SSC7 | 0.804 | | | | |
| | SSC8 | 0.799 | | | | |
| | SSC9 | 0.786 | | | | |
| | SSC10 | 0.786 | | | | |
| | SSC11 | 0.762 | | | | |
| | SSC12 | 0.823 | | | | |
| | SSC13 | 0.801 | | | | |
| | SSC14 | 0.774 | | | | |

From the preliminary analysis, it has been determined that the measurement model for SSC PERF was reliable and valid as it achieved strong indicator reliability with most loadings higher than 0.7. Item SSC1 was deemed concerning, but a further assessment was done based on C.R. and AVE, which were all in the acceptable range. We noted acceptable internal consistency reliability with Cronbach's alpha and C.R. higher than 0.7 and convergent validity with AVE values for all three first-order constructs higher than 0.5. In Table 5.8, we present the measurement model of SSC PERF as a second-order construct.

Table 5.8 Preliminary measurement model for sustainability performance

| Second-Order Construct | First-Order Constructs (Reflective) | Items | Factor Loading | Cronbach's Alpha | rho_A | C.R. | AVE |
|---|---|---|---|---|---|---|---|
| **Sustainability Performance** | Economic | SSC1 | 0.744 | 0.830 | 0.839 | 0.887 | 0.663 |
| | | SSC2 | 0.862 | | | | |
| | | SSC3 | 0.879 | | | | |
| | | SSC4 | 0.763 | | | | |
| | Environmental | SSC5 | 0.840 | 0.909 | 0.909 | 0.932 | 0.734 |
| | | SSC6 | 0.880 | | | | |
| | | SSC7 | 0.902 | | | | |
| | | SSC8 | 0.872 | | | | |
| | | SSC9 | 0.786 | | | | |
| | Social | SSC10 | 0.851 | 0.912 | 0.913 | 0.934 | 0.740 |
| | | SSC11 | 0.852 | | | | |
| | | SSC12 | 0.857 | | | | |
| | | SSC13 | 0.883 | | | | |
| | | SSC14 | 0.859 | | | | |

Through our assessment of the reliability and validity of first-order constructs – Economic, Environmental, and Social Sustainability Performance, we concluded that all constructs achieved the desired indicator reliability as factor loadings were mostly above the recommended level for reflective models. Our constructs attained the desired internal consistency reliability with Cronbach's alpha, rho_A, and C.R. values above 0.7. With an AVE value of 0.5, we concluded that the SSC PERF model achieved convergent validity. We identified no items for deletion in the observed measures.

Table 5.9 Measurement model for sustainability performance

| Second-Order Construct | First-Order Constructs (Reflective) | Factor Loading | T-statistics | p-values | Significant? |
|---|---|---|---|---|---|
| **Sustainability Performance** | Economic | 0.768 | 21.43 | 0.000 | Yes |
| | Environmental | 0.928 | 82.38 | 0.000 | Yes |
| | Social | 0.918 | 74.22 | 0.000 | Yes |

The measurement model for sustainability performance revealed that all three first-order constructs were true reflective measures of this construct. All constructs returned factor loadings higher than 0.7 and returned a significant p-value and t-statistics above 1.96. With the reliability constructs established, we assess the discriminant validity of constructs to determine the extent to which the constructs are genuinely distinct from one another on the basis of empirical standards (Hair et al., 2017).

***Discriminant validity assessments***

Assessing discriminant validity confirms that each construct is distinct from the others and does not measure the same thing. As indicated earlier in this chapter, discriminant validity was assessed using three common methods widely discussed in the literature. First, I assessed the cross-loadings and expected that the outer loading for a given construct should be greater than that of others. Then, the Fornell-Larcker Criteria, which requires that the square root of the AVE is greater than the correlation between constructs, has been presented. Lastly, I considered the HTMT ratio, a strongly recommended approach for PLS-SEM, as it produces better validity results than the first two approaches.

Table 5.10 Discriminant validity by cross-loadings

| | BDAC | COST | QUAL | DELI | SERV | TECH | ECON | ENVI | SOCI |
|---|---|---|---|---|---|---|---|---|---|
| **BDAC1** | **0.815** | 0.237 | 0.424 | 0.304 | 0.117 | 0.319 | 0.403 | 0.443 | 0.457 |
| **BDAC2** | **0.452** | 0.072 | 0.156 | 0.116 | -0.035 | 0.028 | 0.098 | 0.115 | 0.141 |
| **BDAC3** | **0.787** | 0.177 | 0.363 | 0.238 | 0.140 | 0.219 | 0.256 | 0.374 | 0.389 |
| **BDAC4** | **0.372** | -0.010 | 0.012 | 0.055 | -0.043 | 0.012 | 0.094 | 0.081 | 0.131 |
| **BDAC5** | **0.493** | 0.056 | 0.171 | 0.157 | 0.066 | 0.044 | 0.052 | 0.113 | 0.136 |
| **BDAC6** | **0.778** | 0.179 | 0.410 | 0.303 | 0.082 | 0.212 | 0.344 | 0.514 | 0.520 |
| **BDAC7** | **0.644** | 0.143 | 0.335 | 0.379 | 0.104 | 0.092 | 0.250 | 0.308 | 0.366 |
| **BDAC8** | **0.811** | 0.211 | 0.426 | 0.282 | 0.120 | 0.241 | 0.296 | 0.416 | 0.431 |
| **PO1** | 0.239 | **0.797** | 0.330 | 0.219 | 0.143 | 0.231 | 0.218 | 0.134 | 0.159 |
| **PO2** | 0.109 | **0.787** | 0.255 | 0.172 | 0.138 | 0.252 | 0.280 | 0.193 | 0.211 |
| **PO3** | 0.212 | **0.801** | 0.300 | 0.244 | 0.078 | 0.209 | 0.259 | 0.245 | 0.246 |
| **PO4** | 0.345 | 0.284 | **0.743** | 0.361 | 0.260 | 0.397 | 0.302 | 0.317 | 0.334 |
| **PO5** | 0.428 | 0.343 | **0.856** | 0.560 | 0.355 | 0.356 | 0.362 | 0.507 | 0.448 |
| **PO6** | 0.382 | 0.244 | **0.748** | 0.533 | 0.212 | 0.321 | 0.362 | 0.425 | 0.403 |
| **PO7** | 0.339 | 0.187 | 0.511 | **0.834** | 0.200 | 0.225 | 0.352 | 0.420 | 0.468 |
| **PO8** | 0.354 | 0.254 | 0.610 | **0.886** | 0.381 | 0.383 | 0.414 | 0.492 | 0.459 |
| **PO9** | 0.216 | 0.208 | 0.374 | **0.725** | 0.251 | 0.162 | 0.309 | 0.354 | 0.328 |
| **PO10** | 0.128 | 0.115 | 0.350 | 0.359 | **0.884** | 0.510 | 0.253 | 0.235 | 0.170 |
| **PO11** | 0.106 | 0.151 | 0.275 | 0.252 | **0.876** | 0.616 | 0.339 | 0.234 | 0.173 |
| **PO12** | 0.169 | 0.277 | 0.365 | 0.255 | 0.629 | **0.837** | 0.430 | 0.266 | 0.233 |
| **PO13** | 0.192 | 0.142 | 0.299 | 0.205 | 0.482 | **0.829** | 0.325 | 0.158 | 0.188 |
| **PO14** | 0.309 | 0.292 | 0.463 | 0.354 | 0.493 | **0.849** | 0.356 | 0.325 | 0.291 |
| **SSC1** | 0.280 | 0.214 | 0.318 | 0.355 | 0.312 | 0.418 | **0.745** | 0.343 | 0.344 |
| **SSC2** | 0.296 | 0.203 | 0.303 | 0.343 | 0.316 | 0.382 | **0.862** | 0.473 | 0.420 |
| **SSC3** | 0.276 | 0.254 | 0.360 | 0.355 | 0.279 | 0.350 | **0.879** | 0.543 | 0.427 |
| **SSC4** | 0.401 | 0.340 | 0.425 | 0.387 | 0.202 | 0.314 | **0.763** | 0.548 | 0.603 |
| **SSC5** | 0.405 | 0.240 | 0.419 | 0.469 | 0.213 | 0.249 | 0.558 | **0.840** | 0.609 |
| **SSC6** | 0.441 | 0.220 | 0.471 | 0.451 | 0.258 | 0.281 | 0.549 | **0.879** | 0.654 |
| **SSC7** | 0.457 | 0.184 | 0.466 | 0.428 | 0.277 | 0.254 | 0.494 | **0.902** | 0.659 |
| **SSC8** | 0.457 | 0.200 | 0.475 | 0.421 | 0.206 | 0.272 | 0.481 | **0.872** | 0.686 |
| **SSC9** | 0.447 | 0.178 | 0.466 | 0.469 | 0.184 | 0.250 | 0.476 | **0.786** | 0.746 |
| **SSC10** | 0.502 | 0.230 | 0.459 | 0.507 | 0.143 | 0.229 | 0.478 | 0.679 | **0.851** |
| **SSC11** | 0.449 | 0.230 | 0.444 | 0.424 | 0.170 | 0.263 | 0.473 | 0.626 | **0.852** |
| **SSC12** | 0.516 | 0.233 | 0.452 | 0.448 | 0.203 | 0.288 | 0.496 | 0.747 | **0.857** |
| **SSC13** | 0.471 | 0.208 | 0.395 | 0.412 | 0.206 | 0.268 | 0.494 | 0.672 | **0.883** |
| **SSC14** | 0.402 | 0.204 | 0.428 | 0.428 | 0.112 | 0.187 | 0.478 | 0.643 | **0.859** |

The cross-loadings in Table 5.10 reveal acceptable discriminant validity with higher loadings on respective constructs. In a few cases, we noted some outer loading higher than 0.7. For instance, indicator SSC9 for the environmental sustainability construct shows a 0.746 loading on the social sustainability construct, but is still lower than other indicators. Also, the indicator SSC12 of the social sustainability construct shows a 0.747 loading on the environmental

sustainability construct. These values could raise discriminant validity concerns; however cross loading is not the best way to conclude discriminant validity (Hair Jr et al., 2017; Henseler et al., 2015). Hence, we further assessed discriminant validity based on the Fornell-Larcker Criterion (Table 5.11) and HTMT ratio (Table 5.12).

Table 5.11 Discriminant validity by Fornell-Larcker Criterion

| | BDAC | COST | DELI | ECON | ENVI | QUAL | SERV | SOCI | TECH |
|---|---|---|---|---|---|---|---|---|---|
| **BDAC** | **(0.666)** | | | | | | | | |
| **COST** | 0.237 | (0.795) | | | | | | | |
| **DELI** | 0.378 | 0.267 | **(0.817)** | | | | | | |
| **ECON** | 0.389 | 0.316 | 0.443 | (0.814) | | | | | |
| **ENVI** | 0.516 | 0.239 | 0.523 | 0.597 | (0.857) | | | | |
| **QUAL** | 0.493 | 0.373 | 0.623 | 0.437 | 0.537 | (0.784) | | | |
| **SERV** | 0.133 | 0.151 | 0.348 | 0.335 | 0.266 | 0.356 | (0.880) | | |
| **SOCI** | 0.545 | 0.257 | 0.516 | 0.563 | 0.784 | 0.506 | 0.195 | (0.860) | |
| **TECH** | 0.271 | 0.290 | 0.329 | 0.444 | 0.305 | 0.455 | 0.639 | 0.287 | **(0.838)** |

Our assessment of the Fornell-Larcker criterion indicated acceptable discriminant validity as the square roots for all construct AVE (the values in parentheses) are greater than the correlation between constructs. This criterion has been criticised for inaccurate determination of discriminant validity, in a widely accepted study by (Henseler et al., 2015) – I applied the HTMT ratio assessment. The ratios are presented in Table 5.12.

Table 5.12 Discriminant validity by HTMT

| | BDAC | COST | DELI | ECON | ENVI | QUAL | SERV | SOCI | TECH |
|---|---|---|---|---|---|---|---|---|---|
| **BDAC** | | | | | | | | | |
| **COST** | 0.271 | | | | | | | | |
| **DELI** | 0.421 | 0.362 | | | | | | | |
| **ECON** | 0.397 | 0.407 | 0.555 | | | | | | |
| **ENVI** | 0.500 | 0.299 | 0.626 | 0.676 | | | | | |
| **QUAL** | 0.564 | 0.530 | 0.845 | 0.574 | 0.675 | | | | |
| **SERV** | 0.169 | 0.213 | 0.463 | 0.446 | 0.331 | 0.505 | | | |
| **SOCI** | 0.542 | 0.321 | 0.618 | 0.633 | 0.860 | 0.638 | 0.241 | | |
| **TECH** | 0.264 | 0.378 | 0.400 | 0.553 | 0.351 | 0.612 | 0.853 | 0.333 | |

The HTMT assessment confirmed discriminant validity between variables in the model. (Henseler et al., 2015) indicated that a liberal HTMT criterion, such as $HTMT_{.90}$ is warranted. Following these guidelines, we observed that all values in the Table above are less than 0.90, confirming discriminant validity. All three discriminant validity tests confirmed that the constructs were distinct from one another.

## 5.4 Final Model Estimation

Although discriminant validity was established, a few observable items revealed potential indicator reliability and convergent validity issues. Consequently, another model estimation was undertaken. In the final model, we removed observable items that inhibited BDAC indicator reliability and validity. PPO and SCC PERF achieved acceptable reliability; thus, no observable items were eliminated for these constructs. The final model estimation is presented in Figure 5.13.

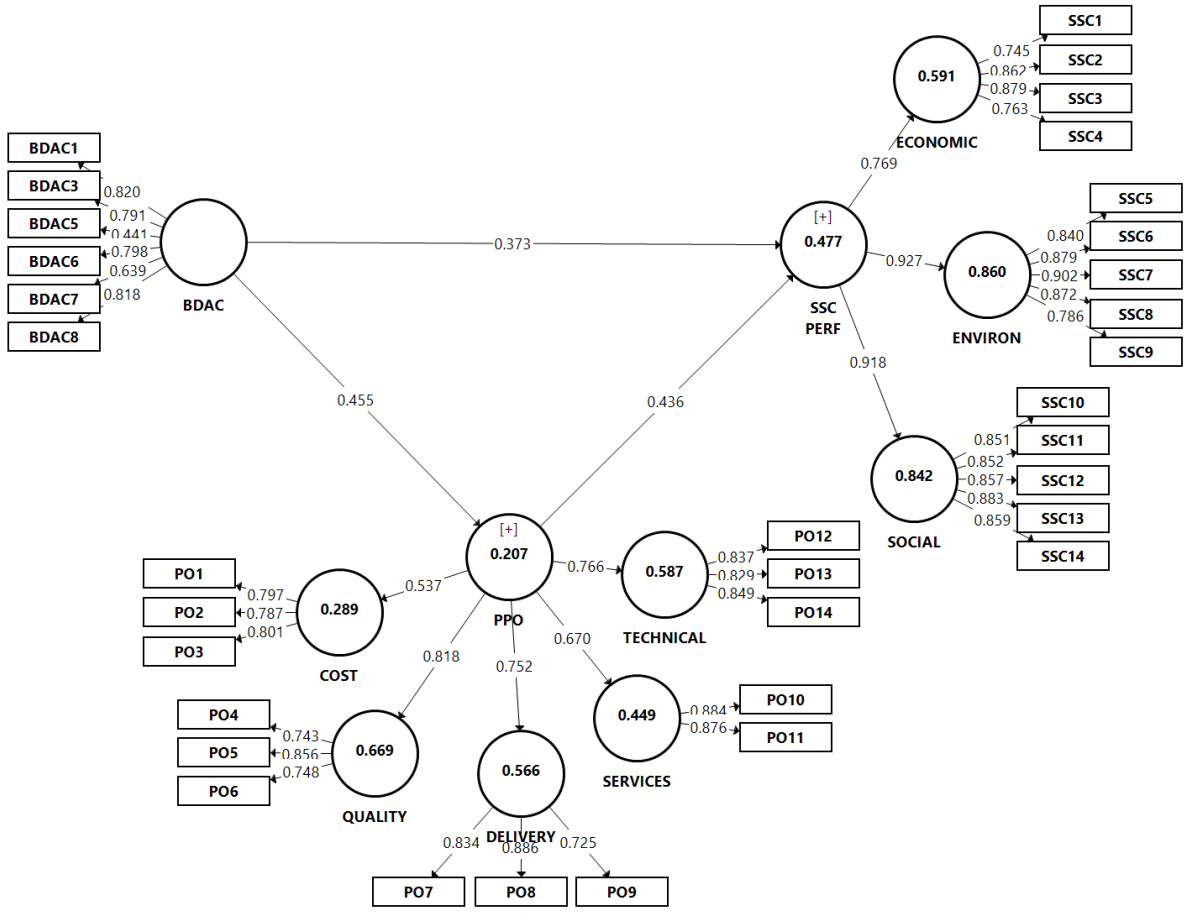



Figure 5.13 Final model estimation

### *Big data analytics capability*

As earlier indicated, the BDAC construct failed the validity and reliability tests, necessitating an indicator reliability test. This test involved assessing outer loadings and deleting indicators to improve indicator reliability and convergent validity. Items were only deleted when such deletion improved the construct convergent validity. Regarding BDAC, two indicators were eliminated; BDAC4 was removed first because it had the lowest outer loading of 0.372, and

the deletion increased AVE from 0.443 to 0.485. Since the AVE was still below the 0.5 threshold, I deleted indicator BDAC2, which had the second lowest outer loading of 0.452 and increased the AVE to 0.535 (See Table 5.13). Increasing AVE to 0.535 indicated that the BDAC construct achieved acceptable convergent validity, which meant that the measures used for BDAC (i.e., BDAC1, BDAC3, BDAC5-8) are theoretically related. No other items were deleted after the construct achieved acceptable convergent validity and internal consistency reliability. The absolute reliability and validity assessments are summarised in the Table below.

Table 5.13 A measurement model for BDAC

| Latent Variable | Items | Outer Loading | Cronbach's Alpha | rho_A | C.R. | AVE |
|---|---|---|---|---|---|---|
| **Big Data Analytic Capabilities** | BDAC1 | 0.820 | 0.822 | 0.856 | 0.869 | 0.535 |
| | BDAC3 | 0.791 | | | | |
| | BDAC5 | 0.441 | | | | |
| | BDAC6 | 0.798 | | | | |
| | BDAC7 | 0.639 | | | | |
| | BDAC8 | 0.818 | | | | |

It is concluded that the BDAC construct is measured by six observable indicators, including BDAC1 (the organisation is capable of parallel computing to address voluminous data), BDAC3 (the system is capable of handling semi-structured data), BDAC5 (data-driven intelligence has made our decision-making more effective), BDAC6 (Our organisation has good I.T. infrastructure and facilities), BDAC7 (The interchangeability of services such as cloud, mobile, and analytics plays a key role in the organisation), and BDAC8 (analytics personnel are proficient with programming, data management, new tools etc.). The BDAC measurement model achieved internal consistency reliability with Cronbach's alpha and C.R. higher than 0.7 and convergent validity with AVE equal to 0.535.

Table 5.14 Overall reliability and validity assessments for all constructs

| Latent Construct | Items | Loadings | Cronbach's Alpha | rho_A | CR | AVE |
|---|---|---|---|---|---|---|
| **BDAC** | BDAC1 | 0.820 | 0.822 | 0.856 | 0.869 | 0.535 |
| | BDAC3 | 0.791 | | | | |
| | BDAC5 | 0.441 | | | | |
| | BDAC6 | 0.798 | | | | |
| | BDAC7 | 0.639 | | | | |
| | BDAC8 | 0.818 | | | | |
| **PPO** *(Second Order)* | Cost | 0.535 | 0.709 | 0.710 | 0.838 | 0.632 |
| | Quality | 0.806 | 0.658 | 0.697 | 0.827 | 0.615 |
| | Delivery | 0.738 | 0.709 | 0.709 | 0.873 | 0.775 |
| | Service | 0.688 | 0.790 | 0.796 | 0.876 | 0.703 |
| | Technical | 0.780 | 0.751 | 0.788 | 0.857 | 0.668 |
| **SSC PERF** *(Second Order)* | Economic | 0.769 | 0.830 | 0.839 | 0.887 | 0.663 |
| | Environmental | 0.927 | 0.909 | 0.909 | 0.932 | 0.973 |
| | Social | 0.918 | 0.912 | 0.913 | 0.934 | 0.740 |

In Table 5.14, checks for reliability and validity of constructs indicate that the scales are reliable. First, for all latent constructs – BDAC, PPO, and SSC PERF – the average variance extracted (AVE) was above the recommended threshold of 0.5, which suggests that our latent variables explain at least 50% of item variance. It is concluded that our scales achieve the required convergent validity. In addition, the composite reliability (C.R.) and Cronbach alpha show that our measures achieved internal consistency reliability since all C.R. values are greater than 0.7 and Cronbach's alpha is greater than 0.8. Similarly, the rho_A value is greater than 0.7, confirming composite reliability. All three sub-constructs achieved convergent validity with AVE above 0.5, internal consistency reliability with C.R. above 0.7 and Cronbach's alpha and rho_A above 0.8.

SSC PERF's complex nature and novelty suggest that such a variable should be studied considering different dimensions. The existing literature has reported on economic, environmental, and social performance, which we adopted into this study. Therefore, the sustainability performance of the supply chain was measured with a second-order reflective measurement model – reliability and validity results reported earlier in Table 5.14. First, the factor loadings retained were all above 0.7, as widely recommended for reflective measurement models. To this end, we confirmed discriminant validity, as shown in the previous section and eradicated reliability problems. In the preceding sections, I have discussed the structural model and hypothesis tests.

**Structural model and hypothesis tests**

As the reliability and validity have been confirmed, I assessed the structural model, which included evaluating the relationship between constructs (path coefficients), the coefficient of determination ($R^2$), the effect size ($f^2$), and the predictive capabilities of the model – i.e., predictive relevance ($Q^2$). The significance of path coefficients was assessed using the bootstrapping method, in which, according to Hair et al. (2017), the minimum number of bootstrap samples should be about 5000. Figure 5.14 presents this structural model, with a focus on the effects of BDAC on PPO and SSC PERF.

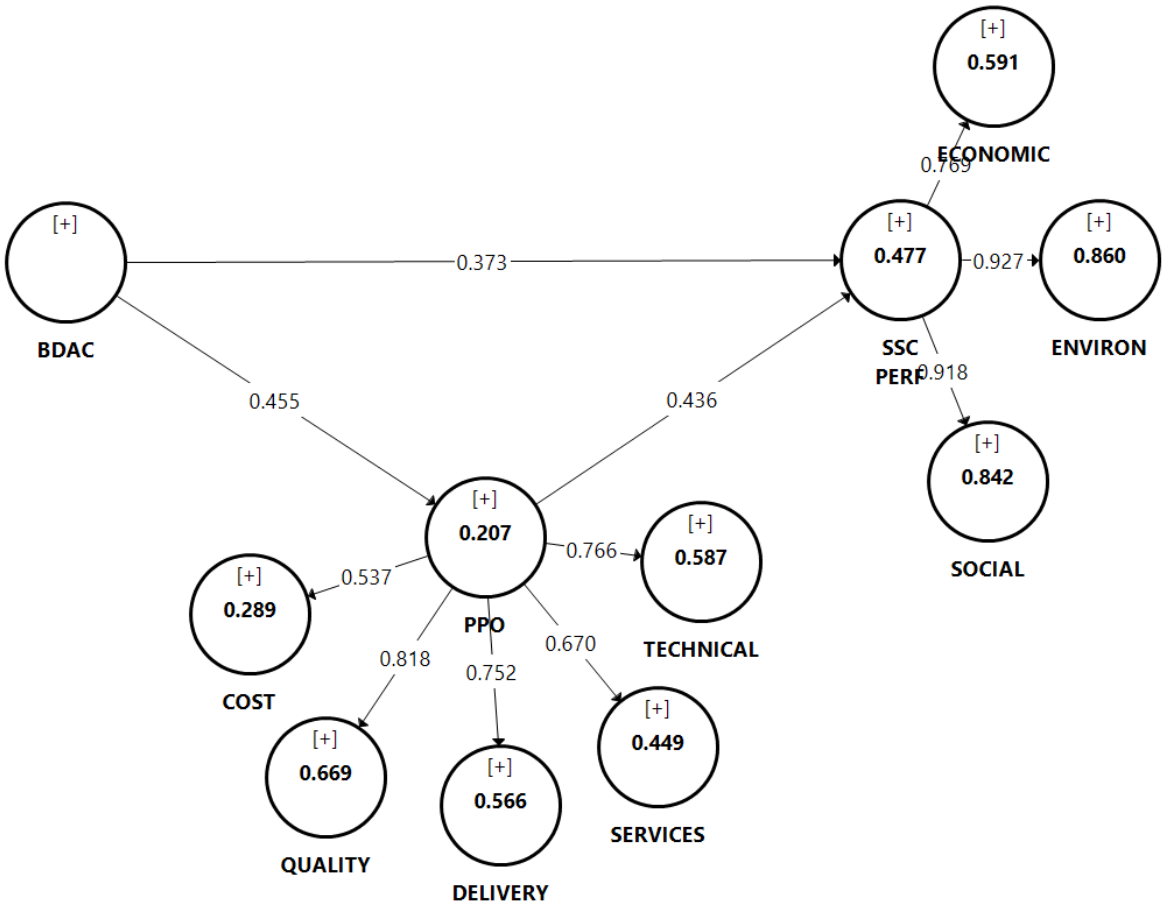



Figure 5.14 Structural model

The structural model assessment follows six steps, including assessing the model for collinearity issues, assessing the significance of the relationships between constructs, assessing the level of $R^2$, assessing the $f^2$ effect size, and assessing the predictive relevance ($Q^2$) (Hair et al., 2017). It is important to note that instead of assessing goodness-of-fit, structural models are assessed to determine their predictive capabilities (Hair et al., 2017). It is emphasised that pursuing model fit offers little value, and researchers could inadvertently sacrifice predictive power to achieve a better fit. This study prioritised construct relationships and the model's predictive power.

### *Collinearity assessment*

Firstly, I assessed the possibility of collinearity problems. Collinearity occurs when a variable is highly correlated with another variable. Collinearity is presumed to increase parameter estimates and produces statistically insignificant variables (O'brien, 2007). The variance inflation factor (VIF) and tolerance are widely acknowledged for assessing collinearity problems. VIF values higher than 5 (Tolerance values below 0.2) in predictor variables indicate

collinearity problems (Hair et al., 2017). Table 16 reveals the VIF values for our predictors BDAC and PPO. All VIF values are lower than 5; thus, the model has no collinearity issues.

Table 5.15 Collinearity statistics (VIF)

| | **VIF** |
|---|---|
| BDAC1 | 2.162 |
| BDAC3 | 2.135 |
| BDAC5 | 1.249 |
| BDAC6 | 1.926 |
| BDAC7 | 1.415 |
| BDAC8 | 2.085 |
| PO1 | 1.357 |
| PO2 | 1.391 |
| PO3 | 1.544 |
| PO4 | 1.315 |
| PO5 | 1.940 |
| PO6 | 1.304 |
| PO7 | 1.818 |
| PO8 | 1.766 |
| PO9 | 1.446 |
| PO10 | 1.778 |
| PO11 | 1.432 |
| PO12 | 2.179 |
| PO13 | 1.744 |
| PO14 | 2.038 |

***Direct effect assessment***

The second step was to assess the hypothesised relationships between constructs, particularly the effect of BDAC on PPO and SSC PERF, as well as the effect of PPO on SSC PERF. In Table 5.16, I summarised the observed effects of BDAC on PPO and SSC PERF and whether those effects are statistically significant.

Table 5.16 Structural model results

| **Hn** | **Relationship** | **Path Coefficient** | **Std Dev** | **T-Values** | **P-Values** | **Comment** |
|---|---|---|---|---|---|---|
| **H1** | BDAC → SSC PERF | 0.373 | 0.057 | 6.501 | 0.000 | Supported |
| **H2** | BDAC → PPO | 0.455 | 0.053 | 8.566 | 0.000 | Supported |
| **H3** | PPO → SSC PERF | 0.436 | 0.057 | 7.611 | 0.000 | Supported |

The structural model in Figure 1 tested three hypotheses, which stated that BDAC positively affects sustainability performance (H1) and public procurement optimisation (H2). Besides, public procurement optimisation positively affects sustainability performance (H2). Having

established the reliability and validity of measures, we tested the structural model. We found that BDAC has a significant positive effect on sustainability performance ($\beta = 0.373$, $t = 6.501$, $p < 0.01$) and public procurement optimisation ($\beta = 0.455$, $t = 8.566$, $p < 0.01$), which supported H1 and H2. Also, public procurement optimisation significantly positively affects sustainability performance ($\beta = 0.436$, $t = 7.611$, $p < 0.01$), which supports H3.

***Mediation analysis***

Previous mediation was assessed using the Sobel Test, which compares the direct and indirect relationships. The Sobel test was deemed inadequate for PLS-SEM because it assumes normal data distribution, which does not apply to nonparametric PLS-SEM, relies on unstandardized path coefficients and lacks statistical power (Hair et al., 2017). Since the dismissal of the Sobel test, among some others, Preacher and Hayes's (Preacher & Hayes, 2004) the bootstrap method is widely being adopted, and many studies encouraged its use to establish the significance of the indirect effect. Preacher and Hayes (Preacher & Hayes, 2004) argue that a critical element of mediation is a statistically significant indirect effect. Before the mediation analysis, we ensured that the mediator and other constructs passed the discriminant validity test because failure to achieve satisfactory discriminant validity can result in biased indirect effects (Hair et al., 2017). Figure 5.15 shows the structural model with the direct effect.

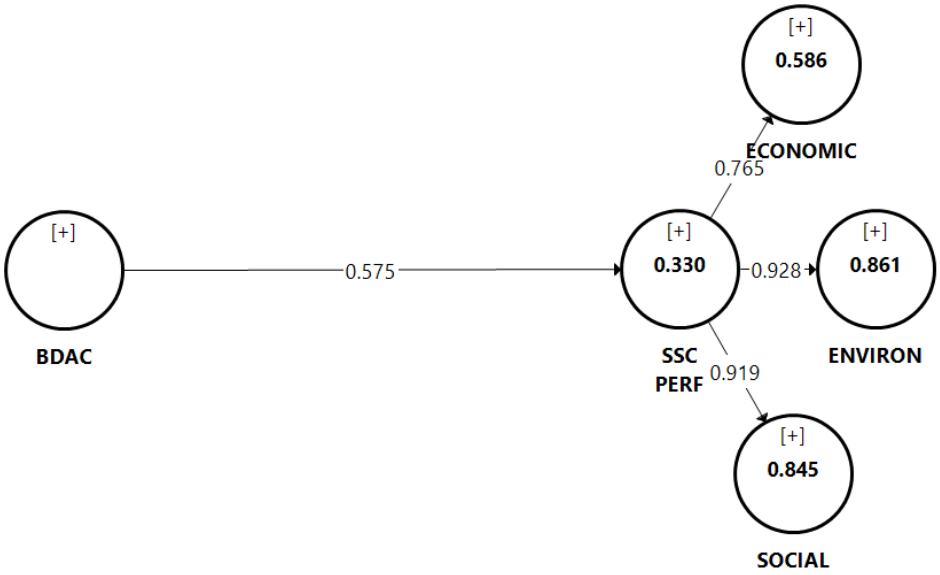



Figure 5.15 Direct effects of BDAC on SSC PERF

Table 5.17 Significance analysis of the direct and indirect effects

| | | Path Coefficient | Indirect Effect | STD | T-Values | P-Values | Comment |
|---|---|---|---|---|---|---|---|
| H4 | Effect (without mediator) | 0.575 | n/a | 0.046 | 12.536 | 0.000 | Partial Mediation |
| | Effect (with mediator) | 0.373 | 0.198 | 0.037 | 5.336 | 0.000 | |

The findings in Table 5.17 provide empirical support for the mediating role of PPO in the model, which supports H4. PPO presents a mechanism that augments the relationship between BDAC and SSC PERF, which implies that PPO can explain the effect of BDAC on SSC PERF. Notably, PPO partially mediates the effect of BDAC on SSC PERF.

***Effect sizes and predictive relevance***

I assessed the model's $f^2$ effect size to determine how much the BDAC and PPO contribute to the $R^2$ value of the sustainability performance. The "effect size assesses the magnitude or strength of the relationship between the variables" (Wong, 2019). I evaluated BDAC's effect size (f2) on SSC PERF and PPO. It was observed that BDAC has a moderate effect size of 0.261 on PPO and 0.211 on SCC PERF. It is noted that PPO has a medium effect size of 0.288 on SCC PERF. Following (Cohen, 1988) 's guidelines on statistical power analyses, an effect size ($f^2$) of 0.02 can be interpreted as small, while 0.15 is medium, and 0.35 is large.

Table 5.18 Results of effect size ($f^2$)

| | SSC PERF | | PPO | |
|---|---|---|---|---|
| | Path Coefficient | $f^2$ effect size | Path Coefficient | $f^2$ effect size |
| BDAC | 0.373 | 0.211 | 0.455 | 0.261 |
| PPO | 0.436 | 0.288 | n/a | n/a |

Lastly, I assessed Stone-Geisser's predictive relevance $Q^{2,}$ which is denoted as important in establishing whether the data points of indicators in the BDAC and PPO measurement models can predict SSC performance. In other words, the $Q^2$ values show whether the model has good predictive relevance for the endogenous variables (PPO and SSC PERF). According to (Hair et al. (Hair et al., 2017), a model has good predictive relevance when its $Q^2$ values are higher than 0. The $Q^2$ and $R^2$ values are reported in the Table below.

Table 5.19 Coefficient of determination and predictive relevance results

| **Dependant Variables** | **Coefficient of determination ($R^2$)** | **Predictive Relevance ($Q^2$)** |
|---|---|---|
| SSC PERF | 0.477 | 0.262 |
| PPO | 0.207 | 0.068 |

The model revealed that the $Q^2$ value for SSC PERF is 0.262 and 0.068 for PPO. Since the $Q^2$ values are higher than 0, it is confirmed that the model has good predictive relevance. The last

step in our analysis was to assess the coefficient of determination, which is the value that indicates how the difference in the endogenous variable, i.e., SCC PERF, can be explained by the difference in the exogenous variables, i.e., BDAC and PPO. Overall, the model returned an $R^2$ = 0.477 for SSC PERF, indicating that BDAC and PPO explain 47.7% of the variance in SSC PERF. Also, the model returned an $R^2$ = 0.207 for PPO, indicating that BDAC explains 20.7% of the variance in PPO.

### 5.5 Summary

Out of the responses I received, 225 were usable, representing 10.36%. This response rate may appear low; however, considering the context of the developing country, the rate is quite good. Big data is a comparatively new business pursuit, particularly in developing countries. Therefore, fewer experts are available on this research project's subject matter. Most importantly, the sample size is significantly higher than the minimum size required for PLS (Hair et al., 2017). The spread of responses reflects Bangladesh's healthcare sector stakeholders, as demonstrated by the coefficient of variation.

I conducted a normality test for both indicators and latent constructs. Results indicated that some of the indicators are not normally distributed. Therefore, PLS-SEM and bootstrapping are used for data analysis and testing techniques. Test results of potential method bias and nonresponse bias confirmed that neither of these biases exists. I further assessed the reliability and validity of all construct measures. The outcome confirms that the measurement model meets internal consistency, indicator reliability, convergent validity and discriminant validity criteria. Hence, these results support all of the hypotheses of this research. BDAC enhances healthcare supply chain sustainability directly and indirectly via procurement optimisation. This relationship is partly mediated by procurement optimisation.

# 6. Conclusion

'Big Data' and 'BDA' became well-regarded topics for industry and academic professionals alike. However, many researchers argue that big data provides benefits only if appropriate organisation-wide skills are available to capitalise on the power of big data (Arias-Pérez et al., 2021b; Arunachalam et al., 2018; Cetindamar et al., 2021; Dubey, Gunasekaran, & Childe, 2019; Hao et al., 2019; Henao-García et al., 2021; Lozada et al., 2019; Mikalef et al., 2019b; Munodawafa & Johl, 2019; Rialti et al., 2019; Wamba et al., 2017; Yasmin et al., 2020).
Big Data Analytics Capabilities (BDAC) is widely accepted as a skillset to transform the way firms usually engage in their business (Akter et al., 2016). Significant progress has been reported at the firm level through the application of BDAC-related concepts (Mikalef et al., 2019a, 2019b; Mikalef, Boura, et al., 2020). However, there is still a limited understanding regarding the ways BDA projects' internal dynamics enhance analytical capability or, in other words, BDAC deployment (Hughes & Ball, 2020). In particular, there is a need for additional empirical research to address the link between BDAC and a firm's performance in diversified sectors, including in healthcare. On the other hand, firms' performance is now regarded to encompass wider domains than a mere measurement of economic performance. One of these increasingly significant domains, which has been echoed across the globe, is with respect to the sustainability performance of the firms' supply chains. As has been showcased in Chapter 2, the optimisation of public procurement greatly impacts the overall sustainability of supply chains. Thus, it was chosen in this research to investigate BDAC's impact on healthcare sustainability performance and the mediating role of public procurement optimisation between these two metrics. As investigations within the contexts of developing countries are scarce, Bangladesh was chosen to provide the context for this analysis.

This study explored the following two main quests to fill in this gap:

*(1) Does BDAC enhance the 'sustainability performance' of healthcare supply chains?*
*(2) Does procurement optimisation mediate the impact of BDAC on the 'sustainability performance' of healthcare supply chains?*

BDAC is operationalised to investigate these questions, representing a combination of eight capabilities adopted from existing literature. Furthermore, two other constructs, namely,

procurement optimisation and sustainability performance, are operationalized and tested through the collected data. Three hypotheses were developed to identify direct and indirect relationships between BDAC and healthcare supply chain sustainability, while all of these hypotheses are found having been supported and confirmed by the collected data.

### 6.1. Summary of Results

Hypothesis 1 suggests that a higher level of BDAC impacts the sustainability performance of the healthcare supply chain. The findings confirm previous claims that BDAC positively impacts sustainability performance. As earlier studies dominantly investigated in respect of developed economies, the applicability of the same findings in the context of developing countries, therefore, remains anecdotal. This study confirms that BDAC can enhance the sustainability of the supply chain in developing economies' healthcare systems. A recent study, conducted in the context of a developing country, revealed that BDAC significantly impacts green supply chain performance (Al-Khatib, 2022a), while another study confirmed BDAC to have enhanced the impact of external social capital on circular supply chain performance, eventually enhancing a firm's sustainability performance (Zhou et al., 2024). Another recent study, conducted in the context of Jordan, confirmed that bid data personal capabilities enhance the sustainable performance of the supply chain (Jum'a et al., 2023). A similar study, conducted in the context of Pakistan, also revealed BDAC positively influencing the sustainability performance of the supply chain (Tipu & Fantazy, 2023).

The results of this research also confirmed the mediating role of procurement optimisation on BDAC's positive influence on the 'sustainability performance' of the supply chain [Hypotheses 2 and 3]. This finding supports practitioners' claim (Faccia & Petratos, 2021; Shabani-Naeeni & Ghasemy Yaghin, 2021; Yan & Cao, 2022), that data analytics could help an organisation in respect of optimal resource planning. In similitude to the findings of this research, a recent study also confirmed the existence of a positive relationship between BDAC and resource optimisation (Huang et al., 2022). The results of this research indicated that BDAC can incentivise business managers to optimise resource sourcing, eventually significantly impacting competitive advantage. This finding supports the widely discussed claim that BDAC-based solutions could help organisations to create timely and deeper business insights from big data to enhance organisational performance through the improvement of various business processes, procurement being one of them. As discussed in the literature review and

shown in Appendix A, the role of BDAC in public procurement optimisation remains unexplored. Therefore, the findings of this research produce a pioneering, unique contribution, as there are no directly comparable studies that have produced similar findings.

In summary, a higher level of BDAC within an organisation encourages the production of data-driven decisions. Thus, when a manager makes decisions based on insights from big datasets, the quality of these decisions improves, leading to an improvement in organisational performance. A healthy count of previous studies also revealed similar findings (Akter et al., 2016; Huang et al., 2022). It, therefore, could be concluded that BDAC impacts supply chain sustainability both directly and indirectly. In relation to direct impact, the findings of this research confirm that BDAC can improve the 'sustainability performance' of supply chains in healthcare in developing economies. In respect of indirect impacts, BDAC can also positively impact the 'sustainability performance' of the healthcare supply chain through a prior positive impact on procurement optimisation. These findings confirm that BDAC and supply chain sustainability could positively either influence or be influenced by intermediary mediators.

Hence, it could be concluded that BDAC positively influences sustainability performance both directly and indirectly. Similar findings with the use of different mediators/moderators in the context of developing countries exist in the literature (Behl, 2020a; Dubey, Gunasekaran, & Childe, 2019; Dubey, Gunasekaran, et al., 2020; Dubey, Gunasekaran, Childe, Roubaud, et al., 2019; Liu & Mehandjiev, 2020; Rialti et al., 2019). This research reconfirms their findings for a rarely analysed business process, namely, procurement.

An extension of these findings could be in terms of the ways BDAC aligns with evolving healthcare regulations and international standards in relation to sustainable procurement. The demonstrated effect of BDAC on sustainability not only indicates to operational needs but also aligns with global goals, such as the United Nations Sustainable Development Goals (SDGs), relevant to good health, well-being, and responsible consumption. By supporting procurement transparency and reducing environmental impact, the adoption of BDAC could potentially lead healthcare organisations to obtain certifications for meeting standards that reinforce a commitment to the exercise of sustainable practices.

The results that have been produced by this research also hint at potential 'positive spillover effects' beyond direct outcomes relating to the supply chain. For instance, enhanced public trust in healthcare procurement processes—fostered by data transparency and accountability—could lead to increased engagement from stakeholders, and eventually foster an environment that

would encourage further public and private investment for the adoption of BDAC-related technologies.

### 6.2 Theoretical Implications

This study makes four main contributions to the existing big data research portfolio. The first contribution is the applicability of the measurement model of BDAC, procurement optimisation, and sustainability performance in the context of a developing country. The constructs that have been utilised in this study are produced on the basis of prior academic studies. However, these constructs are finalised through extensive consultation with industry, academia and public sector managers. Participants' rich academic and industry backgrounds gave a strong foundation to conclude that all operational constructs are aligned with the context of this research. This study is one of the pioneering empirical researches attempting to bring three crucial research streams into one model and, thus, measure BDAC, procurement optimisation, and sustainability in a developing country's context. As per results obtained from a rigorous search in the three most receptive research outlets, namely, Scopus, Google Scholars, and Web of Sciences, no other research attempted to explore BDACs in the context of developing economies, keeping public procurement optimisation as a mediator. BDA implementation in developing countries differs significantly from that of developed countries (Alalawneh & Alkhatib, 2020). For example, there is a considerable difference in infrastructure capital of BDAC between a developed economy and a developing economy (Alalawneh & Alkhatib, 2020; Sánchez Preciado et al., 2016). The change management process of technology adoption also has a differing context (Dubey, Gunasekaran, Childe, Roubaud, et al., 2019; Lin & Kunnathur, 2019; Yu, Wong, et al., 2021). Therefore, the examination of BDA implementation in different contexts carries enormous significance (Lai et al., 2018; Sun et al., 2016; Sun & Sales, 2018).

Even though substantial research in existing literature advocates the benefits of BDA, no empirical study has investigated the ways BDAC impacts public procurement optimisation and, thus, improves the 'sustainability performance' of the healthcare supply chain. Developing countries depend on technologies that are produced in developed economies (Alalawneh & Alkhatib, 2020; Dugstad et al., 2019; Yu, Zhao, et al., 2021). Hence, public procurement of technology or services is key to the management of healthcare facilities in developing countries. Their optimisation, thus, enormously affects the remaining components in the

healthcare system. Therefore, public procurement is an interesting and critical piece of puzzle for the management of BDA for achieving enhanced performance.

The results of this research indicate direct and indirect relationships between BDAC and healthcare supply chain sustainability. This study extends BDAC research by taking an unexplored sector, i.e., public procurement optimisation, as a mediator. As discussed in Chapter 2, gross corruption reported in public procurement in developing countries is alarming. This research can pave the way for the utilisation of the power of BDAC to optimise public procurement, thus helping curb rampant corruption in public sector procurement in developing countries. Models that have been produced in this research also provide a foundation for each construct, such as the identification of the key BDACs that are required to form an organisation's BDACs in the hospital sector, etc.

Secondly, very little is known about the benefits of BDAC in developing countries' public sector, particularly whether public sector managers utilise analytical insights in their day-to-day decision-making. The findings of this research demonstrate that public sector managers in developing countries also rely on BDAC. The enhancement of BDAC in a developing country's healthcare sector could encourage future researchers to explore more areas, thus supplementing the findings of this research.

Thirdly, the hypotheses that have been proposed in this research are empirically tested, enhancing the literature for the development of hypotheses in future investigations. Owing to the use of survey validation, the proposed conceptual and final models also enhance the existing BDAC research portfolio. These contributions, together, present a framework that could be utilised for the design of future research.

Finally, the findings of this research suggest that BDAC impacts all three pillars of sustainability: social, economic, and environmental. BDAC also influences these pillars via its impact on public procurement optimisation. Thus, investing in BDAC can resolve many perennial problems in developing countries, such as environmental pollution, lack of social justice, and optimal use of public funds, etc. The introduction of incentives for managers who tend to rely more on BDAC can foster an increase in the use of BDAC. In the absence of a persistent analytic culture within an organisation, the impact of BDAC would otherwise remain marginal.

Additionally, the integration of BDAC within public procurement frameworks offers a basis for developing new theoretical models that explore digital transformation in public institutions. This study's findings suggest that public procurement when empowered by advanced analytics, serves not just as an operational function but as a strategic driver for the enhancement of institutional transparency and accountability. It, thus, adds a valuable perspective to institutional theory, particularly in the context of developing countries, where resource limitations and governance-related challenges often hinder the appropriation of digital measures.

Moreover, this research prompts consideration of BDAC within a broader framework of organisational resilience. By highlighting BDAC's role in creating flexible and responsive procurement processes, this study contributes to resilience theory, suggesting that data analytics fosters adaptive capacity within supply chains. Future theoretical inputs could explore BDAC's potential in enhancing healthcare-based organisations' ability to anticipate and respond to disruptions, thereby sustaining long-term operational efficiency and sustainability.

### 6.3 Unique Contributions to BDAC in Resource-Constrained Contexts

This study makes a distinctive contribution by examining BDAC in the under-researched context of developing economies, where infrastructural, financial, and skill-related constraints significantly shape the adoption and impact of big data analytics. While prior studies have predominantly focused on BDAC in developed economies (e.g., Mikalef et al., 2019b; Wamba et al., 2017), this research highlights how resource scarcity alters the dynamics of BDAC deployment and its implications for sustainability.

First, the study reveals that BDAC in resource-constrained settings operates under unique contingencies. For instance, unlike in developed economies where advanced IT infrastructure is often assumed, developing countries like Bangladesh face challenges such as fragmented data systems, limited cloud computing adoption, and a shortage of local expertise (Alalawneh & Alkhatib, 2020; Sánchez Preciado et al., 2016). Despite these barriers, the findings demonstrate that even incremental BDAC adoption—such as basic predictive analytics or data-driven procurement tracking—can yield disproportionately high returns for sustainability

performance. This challenges the prevailing narrative that BDAC's benefits are contingent on large-scale investments, offering a pragmatic framework for low-resource settings.

Second, the study redefines procurement optimisation as a critical mediator in such contexts. In developed economies, procurement optimisation often focuses on cost efficiency through automation (Yan & Cao, 2022). However, in Bangladesh's healthcare sector, BDAC-driven procurement addresses systemic issues like corruption, supply chain leakage, and inequitable resource distribution—problems rarely emphasised in prior BDAC literature. By empirically validating the link between BDAC and procurement transparency, this research provides a novel pathway through which analytics can mitigate institutional inefficiencies endemic to developing countries.

Third, the study underscores contextual BDAC capabilities that are pivotal in resource-constrained environments. For example:
Low-cost analytics tools (e.g., open-source platforms like R or Python-based solutions) are prioritised over proprietary systems due to budget limitations.
Human-centric BDAC—such as training frontline staff in basic data literacy—emerges as a critical driver, compensating for gaps in technical infrastructure.
Collaborative data ecosystems (e.g., partnerships between public hospitals and local universities) help overcome skill shortages, a strategy seldom documented in developed-economy studies.

These insights distinguish the study from prior work and offer a blueprint for adapting BDAC frameworks to settings where resources are scarce, but sustainability pressures are acute. By bridging this gap, the research not only advances academic discourse but also provides actionable guidance for policymakers and practitioners in similar contexts.

### 6.4 Managerial Implications

The empirical investigation argues that existing claims on the role of BDAC on a firm's performance in the context of a developed country are also valid in a developing country's context. Moreover, the findings of this research might have the following practical implications for managers.

Firstly, managers might feel more confident in relying upon advanced analytics in their decision-making process. The findings of this research could work as an incentive for managers to decide to increase organisational BDAC. The BDAC constructs of this research should provide a base for managers regarding the underlying components of BDAC that are more aligned to the developing countries' context. Therefore, managers might be able to figure out which areas, tools, methods, culture, etc., are more aligned with their organisation's circumstances.

Secondly, the overall model produced in this research might assist healthcare industries in prioritising components and may consider further in-house research or consultation to realign this model to the best utility of their organisations. This model could act as a primary guide in framing different BDAC implementation strategies for healthcare-based industries.

Thirdly, the findings of this research provide insights to managers regarding the mechanism to deal with BDAC in the real world and realise optimum yield from the use of BDA. Managers and practitioners can figure out organisational gaps in respect of BDAC, and the means to enhance BDAC through the adoption of more sophisticated BDA tools and techniques.

Fourthly, managers can determine the data analytics skills required to form organisational BDAC. They can hire resources from the available market. Also, a long-term in-house capacity-building program could be operationalised to meet the strategic human capital needs of an organisation.

Last but not the least, developing countries lack in adequate framing of technology-related policies. This lack mostly originates from insufficient research findings before policymakers. The findings of this research could help policy stakeholders frame new BDAC, procurement and sustainability-related policies.

The findings of this research also suggest that managers could harness BDAC-based insights to foster partnerships with suppliers and external stakeholders with an aim to enhance sustainability. By sharing relevant analytics-driven data, healthcare organisations can encourage suppliers to align their operations with sustainable practices, thereby extending the impact of BDAC beyond an organisation's internal operations. This approach not only

reinforces sustainability in procurement but also strengthens the overall supply chain by embedding data-driven sustainable practices across relevant partners.

A subsequent managerial consideration would be in respect of the strategic importance of investment in workforce development. As BDAC requires a high level of data literacy, managers should consider implementing training programs to build the competency of staff with respect to the interpretation and application of appropriate analytics. This shift would enable staff to make informed, data-backed decisions at various levels of the supply chain, ensuring that BDAC's potential is optimised across organisational operations.

### 6.5 Research Limitations

This study was conducted to elicit the impact of BDAC on sustainability directly or via optimising public procurement. The focus of this investigation was sustainability and procurement optimisation and the ways these could benefit from BDAC. However, this study has five key limitations.

First, this research is carried out in Bangladesh, which renders the generalizability of these results beyond this region problematic. The conduction of similar studies in different geographical contexts will help identify the extent of the generalisability of these findings.

Second, this study considered patient treatment facilities as 'study areas', although the health sector comprises many sub-sectors. For instance, the medical equipment and pharmaceutical industries constitute a significant part of the healthcare supply chain. Similar studies could, thus, be conducted in other areas of the healthcare sector.

Third, this study relies on expert views, which entails potential biases. The identification of experts with superior knowledge in the pertinent field and eliciting opinions from as many experts as possible could help minimise such biases.

Fourth, although this analysis produces significant findings, these findings should be interpreted with caution. Despite the application of widely accepted statistical methods and the deployment of several statistical remedies in trying to avoid potential biases, in similitude to any survey-based research, this research is also not entirely immune to biases. On the other hand, even though the sample size that has been utilised in this research was significantly more

than what PLS-SEM recommends, there are considerably narrow capabilities for different types of subgroup-based analysis when considered from a broader perspective.

Fifth, due to the technical nature of this research and a long-standing impact by COVID-19, the survey questions were administered in simple manners. For instance, in operationalising various constructs, focus was kept on keeping the questionnaire simple and understandable to the stakeholders in question. Thus, the technical gravity of this questionnaire could be improved in future research.

An additional limitation of this study is the exclusion of real-time data constraints in the context of developing countries. In settings where healthcare data is frequently incomplete or outdated, BDAC might encounter unique challenges that were not fully explored in this study. Future research could examine the ways BDAC capabilities could be tailored or modified to operate effectively with imperfect or delayed data, a common issue in many developing countries.

Lastly, while this study applied a cross-sectional design, future longitudinal studies could provide insights into the ways BDAC impacts healthcare supply chains over time. A longitudinal approach would allow researchers to examine the ways BDAC capabilities evolve as organisations mature in their usage of data, thereby uncovering shifts in its impact on sustainability performance and procurement-related processes.

### 6.6 Future Directions of Research

Four major directions for future research are outlined below.

Firstly, the scope of this study was limited to public-sector tertiary hospitals; therefore, future researchers can extend it to private-sector and field-level public hospitals. On the other hand, this study could be extended to other sub-branches of the healthcare supply chain to get a more representative output, such as in respect of the pharmaceutical industry, pathology, etc. The capability of parallel computing within an organisation helps in processing voluminous data. Hence, it is proposed here that further investigation is carried out to determine whether this positive effect is equally applicable to other sectors. One such investigation could start by considering other branches of the healthcare supply chain.

Secondly, public procurement optimisation has been tested as a mediator between BDAC and sustainability performance. Future researchers could choose other mediators, such as

organisational, analytical culture, level of BDA sophistication, etc., either as mediators or as moderators. Future research could also be extended to test the relationship between BDAC and other organisational perspectives and big data-based features.

Thirdly, future investigations may generate different findings when the proposed conceptual model is tested in another geographical region. Future researchers can explore similar research in other developing countries to test the generalisability of the findings of this research.

Fourthly, future researchers could investigate the ways BDAC could lead to the adoption of innovative practices and innovation within an organisation, thus improving the overall performance of a firm in various other sectors.

### 6.7 Addressing Generalisability Across Healthcare Sub-sectors

A key consideration in extending this research is in respect of the question of its generalisability beyond tertiary hospitals onto other healthcare-related subsectors, including pharmaceuticals, outpatient services, and primary care providers. This study primarily drew from data within tertiary hospital-based settings, which have unique supply chain structures, regulatory considerations, and resource allocations. Although the findings of this research indicate that BDAC positively impacts 'sustainability performance' in hospital supply chains, its direct applicability to other healthcare-based subsectors remains an open question.

In response to this consideration, it could be argued that while the general principles and insights from this research align with healthcare in a broader sense, the unique operational contexts of different subsectors may result in variable outcomes. For instance, pharmaceuticals operate under strict regulatory controls related to product handling and distribution, which may affect the ways BDAC could be leveraged to optimise sustainability-based outcomes. Further empirical research within these subsectors would be essential to validate the relevance and effectiveness of BDAC in varying healthcare-based settings, providing additional robustness to the current findings.

#### 6.7.1 Enhancing generalisability through additional empirical research

To strengthen the applicability of this study's findings, future research could adopt a multi-sector approach, analysing BDAC's impacts across various segments of the healthcare industry.

The conduct of studies in pharmaceutical and primary care-related settings, for instance, would offer a comparative view, shedding light on potential divergences or consistencies in BDAC's role about sustainability. Additionally, sector-specific studies may help refine BDAC frameworks and metrics tailored to the unique demands of each subsector, which, in turn, could support healthcare-wide recommendations for sustainable supply chain optimisation. Another way to enhance generalisability could be through cross-sector collaborations in data collection and analytics. Developing collaborative datasets that encompass diverse healthcare operations would allow researchers to test this study's findings on a broader scale. Such efforts could help confirm whether BDAC's sustainability-related impact is consistently affirmative across settings, or if specific adjustments would be required to optimise its benefits within various sub-sectors.

### 6.8 Empirical Pathways for Ensuring Broader Applicability

Future research could consider longitudinal studies across multiple healthcare providers, tracking BDAC's long-term impact on sustainability within various sub-sectors. By examining the ways BDAC applications evolve over time and in different contexts, researchers could identify whether certain aspects of BDAC are universally applicable or if sector-specific adaptations are necessary. This approach would enable a more nuanced understanding of BDAC's role in healthcare sustainability, contributing to a standardised framework adaptable across healthcare-oriented domains. In addition, the enhancement of generalisability could involve the integration of qualitative insights from key stakeholders in various healthcare-oriented fields. Interviews and case studies with procurement managers, regulatory specialists, and environmental officers in pharmaceuticals or primary care could offer valuable insights, helping in the adaptation and refinement of BDAC strategies in ways that reflect the unique challenges and goals of each subsector.

Ultimately, while this research provides foundational insights into BDAC's role in the healthcare supply chain, its full potential across healthcare settings could only be confirmed through further empirical studies.

# Appendix A : Context Summary of Existing BDAC Research

| BDAC Existing Literature Context | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Author** | **Independent Variable** | **Type** | **Moderator** | **Dependent Variable** | **Mediator** | **Country** | **Sector** | **Sub Sector** | **Does healthcare involve** | **Developed/ Developing*** | **Theory** |
| (Wu et al., 2024) | BDAC | Empirical (n=352) | IT-business Strategic Alignment | Firm Performance | Dynamic Capability | China | Mixed | | | Developed | DCV |
| (Zan et al., 2024) | BDAC | Empirical (n=228) | Environmental Dynamics | Radical Innovation, Incremental Innovation | Improvisational Capabilities | China | | | | Developed | DCV |
| (Al-Khatib & Ramayah, 2023) | BDAC | Empirical (n=420) | Data-Driven Culture | Supply Chain Performance | Supply Chain Innovation | Jordan | Manufacturing | | | Developing | resource-based view (RBV) |
| (Sahoo et al., 2023) | BDAC, Responsible Research and Innovation | Empirical (n=326) | Resource Commitment | Environmental Performance | Circular Economy Practices | India | Manufacturing | | | Developing | DCV |
| (Khan & Fatima, 2024) | BDAC | Empirical (n=350) | Analytics Culture | Firm Performance | Data Integration Capability, Data-Driven Decision Making | Pakistan | Service | | | Developing | RBV |
| (Magableh et al., 2024) | BDAC, Block Chain Adoption | Empirical (n=284) | Environmental Uncertainty | Business Model Innovation | Corporate Entrepreneurship | Australia | Mixed | | | Developed | DCV |
| (Adiguzel et al., 2024) | BDAC | Empirical (n=350) | | Market Performance, Innovation Performance, Financial Performance | Innovation Development, Technology Management | Turkey | Service | | | Developing | |
| (León et al., 2024) | Innovation Performance | Empirical (n=91) | | Business Performance | BDAC | Columbia | Mixed | | | Developing | |
| (Ibrahim et al., 2024) | BDAC | Empirical (n= 179) | | Organisation's Strategic Intent | Environmental Scanning | Egypt | Manufacturing | | Pharmaceuticals | Developing | DCV |
| (Aziz et al., 2024) | BDAC | Empirical (n=115) | | Sustainability Performance of Hotels | Innovation Capability | Malaysia | Service | | | Developing | DCV |
| (Talib et al., 2023) | BDAC [Management Capabilities] | Empirical (n=145) | BDAC [Infrastructure Capabilities], BDAC [Personal Capabilities] | Decision-Making Performance | | UAE | Service | | | Developing | DCV |
| (Faridoon et al., 2024) | BDAC | Empirical (n=120) | | Organisational Performance | Decision Making, Cognitive Style, Organisational Culture | UAE | Services [Gov] | | | Developing | RBV |
| (Zhou et al., 2024) | Social Capital | Empirical (n=414) | BDAC | Sustainable Performance | Circular Supply Chain Management | China | Manufacturing | | Pharmaceuticals and Medical | Developed | social capital theory and resource-based views |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (Pham & Vu, 2024) | BDAC, Blockchain Technology | | | Internationalisation Process | Dynamic Accounting Information System Capability | Vietnam | Mixed | | | Developing | Contingency theory |
| (Lozada et al., 2023) | BDAC | Empirical (n=112) | | Product Innovation Capability, Process Innovation Capability | Absorptive Capability | Columbia | Mixed | | | Developing | |
| (Aziz et al., 2023) | BDAC | Empirical (n=162) | | Marketing Performance, Operational Performance | | Malaysia | Service | | | Developing | resource-based view (RBV) and the contingent resource-based view (CRBV) |
| (Orero-Blat et al., 2024) | Digital Transformation | Empirical (n=183) | | Organisational Performance | BDAC, Innovation | Spain | Services | | | Developed | DCV |
| (Aziz & Long, 2023) | BDAC | Empirical (n=162) | | Exploitative Marketing Capabilities | Explorative Dynamic Capabilities | Malaysia | Service | | | Developing | DCV |
| (Jum'a et al., 2023) | BD Technological Capabilities, BD Personal Capabilities | Empirical (n=207) | | Sustainable Supply Chain Performance | Supply Chain Innovation Capabilities | Jordan | Manufacturing | | | Developing | DCV |
| (Li et al., 2023) | BDAC | Empirical (n=331) | Supply Chain Innovative ness | Sustainable Performance | Green Dynamic Capabilities, Green Supply Chain Performance, Green Competitive Advantages | Pakistan | Manufacturing | | | Developing | RBV |
| (Wang et al., 2024) | BDAC | Empirical (n=354) | | Social Innovation | Knowledge Exploration, Knowledge Exploitation | China | Mixed | | | Developed | Organisational Information Processing Theory, Organisational learning theory |
| (Syafrizal et al., 2023) | Customer Orientation, Entrepreneurial Orientation, Technology Orientation | Empirical (n=191) | | Firm Performance | BDAC, Decision-Making Performance, Competitive Advantage | Malaysia | Manufacturing | | | Developing | RBV |
| (Ansari & Ghasemaghaei, 2023) | BDAC | Meta-Analysis (n= 98) | Performance Type, Country of Origin, Respondent Type | Firm Performance | | | | | | | RBV |
| (Xue et al., 2023) | BDAC | Empirical (n=629) | | Firm Performance | Strategy Flexibility, Strategy Innovation | China | Mixed | | | Developed | RBV, DCV |
| (Brossard et al., 2022) | BDAC | Scoping Review (n=94) | | Value in Hospital | | | | | | | RBV |
| (Wided, 2023) | IT Capabilities | Empirical (n=400) | | Resilience Capabilities | BDAC, Strategic Flexibility | Saudi Arabia | | | | Developing | DCV |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| (Dubey et al., 2021) | Alliance Management Capability | Empirical (n=219) | Information Visibility | Competitive Advantage | BDAC. | India | Manufacturing | | | Developing | DCV |
| (Tongtong & Xinhang, 2024) | Agility | Empirical (n=191) | | Ambidextrous Innovation Capability | BDAC | China | Mixed | | | Developed | RBV, DCV |
| (Shahzad et al., 2022) | Green Supply Chain Management Efforts | Empirical (n=347) | BDAC | Environmental Performance | Operational Performance | Pakistan | Service [Retail] | | | Developing | Natural resource-based view |
| (Zhang & Yuan, 2023) | BDAC | Empirical (n=421) | Environmental Uncertainty | Innovation Performance | Strategic Flexibility, Strategic Innovation | China | Mixed | | | Developed | RBV |
| (Benzidia et al., 2023) | BDAC | Empirical (n=123) | | Environmental Performance | Environmental Process Integration, Green Process Innovation | France | Service | | Hospital | Developed | DCV |
| (Al-Khatib, 2022b) | BDAC | Empirical (n=303) | | Green Supply Chain Performance | Green Supply Chain Innovation, Green Incremental Supply Chain Innovation | Jordan | Manufacturing | | | Developing | RBV and natural resource-based view theory |
| (Zhu et al., 2022) | Internal CSR, External CSR | Empirical (n=320) | | Operational Performance, Environmental Performance | SSCM Practices, BDAC | Pakistan | Manufacturing | | | Developing | DCV, Stakeholder Theory |
| (Fantazy & Tipu, 2023) | BDAC | Empirical (n=300) | | Sustainable Supply Chain Performance | Knowledge Acquisition, Information Distribution, Shared Meaning, Achieved Memory | Pakistan | Manufacturing | | | Developing | DCV |
| (Song et al., 2022) | BDAC [Management and Technology Capability] | Empirical (n=104) | | Competitive Performance [Growth Performance, Financial Performance] | Business Model [Infrastructure Attribute, Value Attribute] | China | Mixed | | | Developed | |
| (Feng et al., 2024) | BDAC | Observation (n= 896) | Technical Risk | Collaboration Innovation Quality | Collaboration Breadth, Collaboration Depth | China | Manufacturing | | | Developed | Knowledge-Based View |
| (Ciacci & Penco, 2023) | Externally Oriented Digital Transformation | Empirical (n=200) | Environmental Hostility | Business Model Innovation | BDAC, | Italy | Mixed | | | Developed | DCV |
| (Bhatti et al., 2022) | BDAC | Empirical (n=221) | | Supply Chain Innovation, Firm Performance | Digital Platform Capabilities, Network Capabilities | Pakistan | Manufacturing | | | Developed | RBV |
| (Huang et al., 2022) | BDAC | Empirical (n=219) | | Competitive Performance | Resource Optimisation, Resource Bricolage | China | Mixed | | | Developed | RBV |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| (Alsmairat, 2023) | Supply Chain Innovation, Customer Readiness, BDAC | Empirical (n=340) | | Digital Supply Chain Performance | Supply Chain Resilience | Jordan | Service | | | Developing | |
| (Naz et al., 2023) | Entrepreneurial Orientation | Empirical (n= 260) | Environmental Dynamism | Hotel Performance | Co-Innovation, BDAC, AIC | Malaysia | Service | | | Developing | entrepreneurial orientation (EO), resource-based view (RBV) theory and Contingent Dynamic Capabilities (CDC) |
| (Makhloufi, 2023) | BDAC | Empirical (n=268) | Knowledge Sharing, Green Organisational Ambidexterity | Green Entrepreneurship Orientation, Eco-innovation | Green Absorptive Capacity | China | Manufacturing | | | Developed | DCV |
| (Munir et al., 2022) | BDAC | Empirical (n=181) | Organisational Culture (OC) and Management accountants | Organisational innovation performance | Process-oriented dynamic capabilities | Pakistan | Manufacturing | | Yes [Pharmaceuticals] | Developing | RBV, Socio-Materiality Theory |
| (Muhammad et al., 2021) | BDAC | Empirical (n=394) | | Firm Innovation Performance | | Pakistan | Service | | | Developing | RBV |
| (Song et al., 2020) | BDAC | Empirical (n=1403 USA 477 China 632 SG 294) | | Sustainable Innovativeness | | USA, China and Singapore | Service Development Project | | | Developed | Information Processing Theory |
| (Chong et al., 2023) | BDAC | Empirical (n= 191) | | Market Performance, Operational Performance | Low-cost Advantage, Differentiation Advantage | Malaysia | Manufacturing | | | Developing | RBV and the entanglement view of sociomaterialism (EVS) theory |
| (Mesquita et al., 2023) | BDAC | Empirical (n=108) | | Sustainability Performance | Lean Technical Practices, Lean Social Practices | Brazil | Manufacturing | | | Developing | Socio-technical System Theory |
| (Tipu & Fantazy, 2023) | BDAC | Empirical (n= 300) | Trust among supply chain partners | Sustainable Supply Chain Performance | Entrepreneurial Orientation | Pakistan | Manufacturing | | | Developing | DCV |
| (Said et al., 2023) | BDAC | Empirical (n=100) | Tone at the top | Sustainability reporting disclosure on Facebook | | Malaysia | Mixed | | | Developing | DCV |
| (Gupta et al., 2023) | BDAC | Empirical (n=218) | Dynamic Capabilities | Sustainability Performance Tourism Supply Chain | | India | Service | | | Developing | RBV |
| (Arias-Pérez et al., 2021a) | Open Innovation | Empirical (n= 112) | | Firm Performance | BDAC | Columbia | Mixed | | | Developing | The knowledge-based view (KBV) |
| (Turi et al., 2023) | Customer knowledge management, | Empirical (n=392) | BDAC | Organisational Performance (OP) | Operational Agility (OA) and strategic agility (SA) | Pakistan | Service | | | Developing | Organisational Learning Theory (OLT), Process theory of the Organisation (PTO), Social |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | Exchange Theory (SET), |
| (Zhang et al., 2020) | BDAC and AIC | Empirical (n=905) | | Success of Sustainability Development Project | | USA and China | Service Sector (Sustainable Development Project) | hotel, travelling, and tourism, banking, insurances, securities, financial investments, information and semiconductors, Internet-related services, health care services | Yes | Developed | Sustainable Development Theory |
| (Morimura & Sakagawa, 2023) | Firm Performance (FP) | Empirical (n= 341) | | Responsive Market Orientation (RMO), Proactive Market Orientation (PMO) | BDAC | Japan | Marketing Service (Retail) | | | Developed | RBV |
| (Su et al., 2021a) | BDAC | Empirical (n=309) | | Organisational Performance | Dual Innovation | China | Manufacturing | | | Developed | RBV |
| (Arshad et al., 2022) | BDAC | Empirical (n=278) | | Sustainable Organisational Development | Autonomous R&D, Absorptive Capacity | China | Service | | | Developed | RBV |
| (Shi et al., 2023) | BDAC | Empirical (n= 317) | Organisation Culture | Green Supply Chain Integration | Supply Chain Visibility | China | Mixed | | | Developed | organisational information processing theory (OIPT) |
| (Olabode et al., 2022) | BDAC | Empirical (n= 458) | Competitive Intensity | Anticipated Financial Performance | Disruptive Business Model, Market Performance | UK | Manufacturing or services | | | Developed | knowledge-based view and contingency theory |
| (Y. Liu et al., 2022) | BDAC | Empirical (n=317) | Data-Driven Decision Culture | Green Supplier Integration, Green Customer Integration | Green Internal Integration | China | Manufacturing | | | Developed | organisational information processing theory |
| (Choi & Park, 2022) | BDA-enabled CSR | Explorative | BDAC | CSR Performance | | Various | | | | | RBV |
| (Ciampi et al., 2021) | BDAC | Empirical (n=253) | al | Business Model Innovation | entrepreneurial orientation | UK | Manufacturing, services, trade and financial industries. | Random selection | | Developed | DCV |
| (Bahrami & Shokouhyar, 2021) | BDAC | Empirical (n=167) | Risk Management Culture | Firm Performance | Innovative capabilities, information quality, Supply chain resilience | Iran | Service | | | Developing | DCV |
| (Behl et al., 2022) | BDAC | Empirical (n= 497) | | Sustainable Competitive Advantage | Supply Chain Coordination, Swift Trust, Supply Chain Risk | India | Service | | | Developing | Information processing theory (OIPT) and Institutional theory (IT) |
| (Dubey et al., 2022) | AI-BDAC | Empirical (n=171) | Information Complexity (IC) | Humanitarian Supply Chain Performance (HSCP) | Humanitarian supply chain agility (HSCA), Humanitarian supply chain resilience (HSCR) | Mixed | Service (NGO) | | | | Practice-based view (PBV) and Contingency theory (CT) |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (Elia et al., 2022) | BDAC | Empirical (n=256) | | Organisational Performance, Business Process Improvement, Product and Services Innovation, Consumer experience and Market Enhancement | Transparency, Access, Discovery, Proactive Adaptation | Italy | Mixed | | | Developed | resource-based view (RBV), dynamic capability view (DCV), and absorptive capacity view (ACV) |
| (Khalil et al., 2023) | BDAC | Empirical (n= 115) | Market Performance, Operational Performance | | Organisational Innovation, Organisational Agility, Marketing Innovation | Malaysia | Service | | | Developing | Knowledge-based view (KBV) and dynamic capability view (DCV) |
| (Chen et al., 2022) | BDAC, IT Business Alignment | Empirical (n= 525) | Event Criticality of COVID-19, Event Disruption of COVID-19 | Decision Outcome | | China | Mixed | | | Developed | DCV |
| (Lozada et al., 2019) | BDAC | Empirical (n=112) | | Co-innovation | | Columbian | Manufacturing and Services | | NO | Developing | |
| (Shamim et al., 2020) | BD Contractual Governance, Big Data Relational Governance | Empirical (n=108) | Data Driven Culture | Decision Making Performance | BDAC | China | Service | online retailing, travel, IT solutions, telecommunication, blockchain technologies and financial services' providers. | NO | Developed | |
| (Bader Khamis AlNuaimi et al., 2021) | E-Procurement | Empirical (n= 216) | | Environment Performance | BDAC (Technological Capabilities and Human Capabilities) | UAE | | Public and Private Organisations who used e-procurement | | Developing [High Income] | Resource orchestration theory |
| (Munodawafa & Johl, 2019) | BDAC | Empirical (n=32) | | Eco-Innovation | | Malaysia | Energy Companies | | NO | Developing | RBV |
| (Liu & Mehandjiev, 2020) | BDAC | Empirical (n=54) | | Firm Performance | Digital Dynamic Capability | China | Consumer-Packaged Goods (CPG) & Retail industries in Chin | | NO | Developed | RBV |
| (Upadhyay & Kumar, 2020) | BDAC | Empirical (n=400) | | Firm Performance | organisational culture and internal analytical knowledge | India | Education | Executive MBA students of premium B-schools | NO | Developing | knowledge management, the sociometrilism theory, the RBV, and DCV |
| (Yasmin et al., 2020) | BDAC | Empirical (n=40) | | Firm Performance | | Pakistan | Manufacturing Firms | | NO | Developing | RBV, DCV |
| (Akter et al., 2016) | BDAC | Empirical (n=152) | Analytics Capability Business Strategy Alignment (ACBSA) | Firm Performance | | USA | Random Manufacturing and Service Firms | | NO | Developed | RBV and the entanglement view of sociomaterialism |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| (Mikalef, Boura, et al., 2020) | BDAC | Empirical (n=175) | Information Governance, Environmental Uncertainty | Incremental innovative capabilities, radical innovative capabilities | | Greece | FI, Consumer Goods, Oil and Gas, Construction and Industrial Goods, ICT, Media, Transport, Shipping, Consumer Service, Basic Materials etc. | | NO | Developed | RBV and Information Governance Theory |
| (Mikalef et al., 2019b) | BDAC | Empirical (n=175) | Environment (Dynamism, Heterogeneity, Hostility) | Incremental Innovation. Radical Innovation | Dynamic Capabilities | Greece | FI, Consumer Goods, Oil and Gas, Construction and Industrial Goods, ICT, Media, Transport, Shipping, Consumer Service, Basic Materials etc. | | NO | Developed | RBV |
| (Ferraris et al., 2019) | BDAC | Empirical (n=88) | | Firm Performance | Knowledge Management | Italy | SMEs | | NO | Developed | RBV |
| (Hooi et al., 2018) | BDAC | Empirical (n=281) | | Product Innovation Performance | | Malaysia | Manufacturing | electrical and electronics companies | NO | Developing | |
| (Dubey, Gunasekaran, & Childe, 2019) | BDAC | Empirical (n=173) | Organisational Flexibility (OF) | Supply chain agility (SCA) and Competitive Advantage (CA) | | India | Manufacturing | Automotive Components Manufacturers Association (India) | NO | Developing | DCV |
| (Shokouhyar et al., 2020) | BDAC | Empirical (n=408) | | Supply Chain Sustainability | | Iran | Manufacturing | Pharmaceuticals | No | Developing | |
| (D. Zhang et al., 2019, 2022) | BDAC | Empirical (n=20) | | Sustainability (Air Pollution management) | | China | Environment | BTH region | NO | Developed | RBV |
| (Ramadan et al., 2020) | BDAC | Empirical (n=117) | Data Availability (DA) | **Sustainable** Competitive Advantage (SCA) | Innovation Capability | Not Mentioned | Manufacturing | | | | DCV |
| (Hao et al., 2019) | BD, BDAC | Empirical (n=1109 USA 477 China 632) | BDAC | Sustainability of Innovation and Organisational Development | BDAC | USA and China | | hotel, travelling, and tourism services; banking, insurances, securities, financial investments, and related activities; information and semiconductor; Internet related-services; health care services | Yes | Developed | RBV |
| (Jha et al., 2020) | BDAC | Qualitative Explorative | | Competitive Advantage (Supply Chain) | | France and India | Economy | 14 companies from both service and Manufacturing sectors | No | Developed and Developing | |
| (Xiao et al., 2020) | BDAC | Empirical (n=175) | Digital Platform Capabilities, Environmental Dynamism | Service Innovation | Dynamic Capabilities | China | Service and Manufacturing | | NO | Developed | DCV |
| (Ashaari et al., 2020) | BDAC | Conceptual (Research Framework) | Continuous Process Innovation | Performance of Higher | | Malaysia | Service | Higher Education | NO | Developing | RBV |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Education Institutions | | | | | | | |
| (Rialti et al., 2019) | BDAC | Empirical (n=259) | Organisation information management system-Fit, Organisational Resistance to information management | Firm Performance | Organisational Agility, organisational ambidexterity | Europe | Manufacturing and Service | | 12.2% Pharmaceuticals and General Healthcare | Developed | |
| (Wamba et al., 2017) | BDAC | Empirical (n=297) | | Firm Performance (FP, MP) | Process Oriented Dynamic Capability | China | Manufacturing and Service | | NO | Developed | RBV |
| (Mikalef et al., 2019a) | BDAC | Empirical (n=175) | | Firm Performance | | Greece | Industrial and services | | No | Developed | Complexity Theory |
| (Arunachalam et al., 2018) | BDAC | bibliometric and thematic analysis | | Issues, Challenge and Implication in Practice | | | | | | | theory of diffusion of innovation and stages of assimilation |
| (Belhadi et al., 2020) | BDAC, Lean Six Sigma Effort, GM Practice | Empirical (n=201) | | **Environmental** Performance | GM Practice, LSS Effort | North Africa | Manufacturing | | NO | Developing | RBV |
| (Mandal, 2018, 2019) | BDA Management Capabilities | Empirical (n=249) | | supply chainpreparedness, SUPPLY CHAIN alertness, supply chain agility | | India | Manufacturing, Construction, Retail, Textile | | NO | Developing | DCV |
| (Sun & Liu, 2020) | Business Model Novelty Design and BM Efficiency Design | Empirical (n=208) | BDA Technology Capability, BDA Management Capability | New Product Development Performance | | China | Service Industry and Manufacturing Industry | | NO | Developed | competence-based view theory |
| (Behl, 2020b) | BDAC | Empirical (n=520) | Organisational Culture, Innovation | Firm Performance of Tech Start UP | Competitive Advantage | India and China | Technology Start-up | | Yes (Healthtech StartUP) 12% of the sample | Developing and Developed | DCV |
| (Bag, Wood, Xu, et al., 2020) | BDAC Management Capability, BDA Talent Capability | Empirical (n=520) | Supply Chain Innovativeness | **Sustainable** supply chain performance | Innovative Green Product Development, Employee Development, Innovation and learning performance | South Africa | Mining Industry | | NO | Developing | DCV |
| (Lin & Kunnathur, 2019) | Customer Orientation, Entrepreneurial Orientation and Technology Orientation, Development Culture | Empirical (n=251) | Developmental Culture | BDAC | | USA | manufacturing, IT, finance, automotive, telecommunications, construction, logistics, retail, media, healthcare, | | NO | Developed | DCV |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | aerospace, utilities, chemical, consulting, and<br><br>Consumer products. | | | | |
| (Wang & Hajli, 2017) | BDAC | Case based Explorative (n=109 cases) | | Business Value | Big Data Analytics Components, BDAC, Benefit Dimension | UK | Healthcare | | Yes | Developed | RBV and CBV |
| (Dubey, Gunasekaran, Childe, Roubaud, et al., 2019) | BDAC | Empirical (n=373) | Flexible Orientation (FO), Control Orientation (CO) | Collaborative Performance (CP) | Swift Trust (ST) | Countries from Asia, including Bangladesh Europe, Africa | Military, Aid Agency, International NGO, Volunteers, Service Providers | | NO | Mixed | *Organisational information processing theory* |
| (Wang et al., 2020) | Internal CSR, External CSR | Empirical (n=260) | BDAC | Firm Performance | Green Supply Chain management | China | Manufacturing | IT, Pharmaceutical,<br><br>Bioengineering, Engineering, Material, Others | NO | Developed | Stakeholder Theory |
| (Jeble et al., 2018) | Big Data and Predictive Capability | Empirical (n=205) | Supply base Complexity | SCS Environment Performance, SCS Social Performance, SCS Economic Performance | | India | Manufacturing | Auto Component Manufacturing Company | NO | Developing | RBV and DCV |
| (Srimarut & Mekhum, 2020) | Supply Chain Connectivity | Empirical (n=233) | | supply chain Agility, supply chain Adaptability, supply chain Alignment | BDAC | Thailand | Manufacturing | | NO | Developing | RBV |
| (Gupta & George, 2016) | BDAC | Empirical (n=232 and 108) | | Firm Market Performance, Firm Operational Performance | | USA | Manufacturing and Service | IT, Finance, Manufacturing, Healthcare, Retail and wholesale, others | Yes (5%) | Developed | RBV |

## Appendix B: Survey Instrument

**Online Survey Questionnaire**

**Research Title**: Big Data Analytics Capability and Healthcare Sustainable Supply Chain: Mediating Role of Public Procurement Optimisation

A full description of the research framework is available here. [Open in a separate tab if error prompts]

**Introduction:**

The study aims to identify the impact of Big Data Analytics Capability (BDAC) on the sustainability performance of the healthcare supply chain and the mediating role of public procurement optimisation between BDAC and the sustainability performance of the healthcare supply chain. The introductory section of the questionnaire will request some demographic information. The main questionnaire is divided into three blocks.

Block one (Questions 1-8) will request your opinion on Big Data Analytics Capabilities (BDAC). This block will identify your organisational strength in accessing and using big data and capabilities to analyze big data. The questions are mostly related to what tools and techniques organisations currently or in the recent past used.
Block two (Questions 9-22) will request your valuable opinion on the impact of having organisation BDAC on procurement optimisation. This section identifies if the procurement process benefits from data tools and techniques.
Block three (Questions 23 -36) will request your valuable opinion on the impact of having organisational BDAC on healthcare supply chain sustainability.

**Consent:**

1) I am 18 Years old (or above). I agree to participate in the research project " Big Data Analytics Capability and Healthcare Sustainable Supply Chain: Mediating Role of Public Procurement Optimisation" UTS ETH21-5833 conducted by Md Ahsan Uddin Murad, 133449222@student.uts.edu.au.

2) I have read the Participant Information Sheet, or someone has read it to me in a language I understand. I understand the research's purposes, procedures and risks as described in the Participant Information Sheet [open in a separate tab if not accessible]. I have had an opportunity to ask questions and am satisfied with my answers. I freely agree to participate in this research project as described and understand that I am free to withdraw at any time without affecting my relationship with the researchers or the University of Technology Sydney.

3) I agree that the research data gathered from this project may be published in a form that does not identify me in any way.

4) I am aware that I can contact Md Ahsan Uddin Murad if I have any concerns about the research.

**If you wish to proceed with the survey, please follow the prompt. Otherwise, you can exit the survey by closing your browser.**

- ○ I agree with the terms and conditions and hereby agree to participate in this research.

**Section One: Demographic information.**

In this section, you will be requested to provide some demographic information. All information provided will be used as UTS and Australian Privacy policy. The demographic information you provide will be used exclusively for analysis and sampling.

Q: What Gender do you identify as?

- Female (1)
- Male (2)
- Others (3)
- I do not know (4)
- Prefer not to say (5)

Q: What is your age?

- 18-25 (2)
- 26-35 (3)
- 36-45 (4)
- 45+ (5)
- Prefer not to say (6)

Q: In what category do you belong? (please tick more than one if applicable)

- ☐ Hospital (1)
- ☐ Clinic (2)
- ☐ Supplier (3)
- ☐ Buyer (4)
- ☐ Academician (5)
- ☐ Civil Society (6)
- ☐ IT professional (7)
- ☐ Government (8)
- ☐ Others (Please specify) (9) _____

Q: Current level of Education?

- PhD (1)
- Masters (2)
- Bachelor (3)
- Diploma (4)
- Others (5)

Q: Occupational Education and Degree (Major)

- Medicine (2)
- Engineering (3)
- Management (4)

- Computer Science (5)
- Others (Please Specify) (6) _____

Q: What is your business location?

- Dhaka (1)
- Chittagong (2)
- Rajshahi (3)
- Khulna (4)
- Barishal (5)
- Mymenshing (6)
- Others (Please Specify) (7) _____

Q: Experience in tech sector?

- 1-3 years (1)
- 3-5 years (2)
- 5-7 years (3)
- 7-10 years (4)
- More than ten years (5)

Q: Experience in using any type of data analytics (Excel, SPSS, Tableau, etc.) in decision making.

- 1-3 years (1)
- 3-5 years (2)
- 5-7 years (3)
- 7-10 years (4)
- More than ten years (5)

Q: Organisation Name

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Q: What is your current role?

- Doctor (2)
- Manager (3)
- Director (4)
- Faculty Member (5)
- Civil Servant (6)
- Owner (8)
- Managing Director (9)
- Others (Please Specify) (10) _____

Block one (Questions 1-8) will request your opinion on Big Data Analytics Capabilities (BDAC). This block will identify the organisational strength in accessing and using Big data and capabilities to analyze big data.

| | Strongly Agree (1) | Agree (2) | Neutral (3) | Disagree (4) | Strongly Disagree (5) |
|---|---|---|---|---|---|
| Q1: Our organisation is capable of parallel computing to address voluminous data. | o | o | o | o | o |
| Q2: Real-time assess of data and information has helped organisation in better decision making. | o | o | o | o | o |
| Q3: Our system is capable of handling semi-structured and unstructured data. | o | o | o | o | o |
| Q4: Truthfulness and accuracy of data have helped our organisation. | o | o | o | o | o |
| Q5: Data-driven intelligence has made our decision making more effective. | o | o | o | o | o |
| Q6: Our organisation has good IT infrastructure and facilities. | o | o | o | o | o |
| Q7: The interchangeability of services (cloud, mobile, and analytics) plays a key role in our organisation. | o | o | o | o | o |
| Q8: Our analytics personnel are proficient with programming, data management, new tools etc. | o | o | o | o | o |

Procurement Optimisation (Q 9-22).

Questions 9-22 identify how BDAC (such as using data analytics tools, i.e. e-GP, SPSS, Excel) helps your organisation or department (or a firm in general) optimize procurement.

You will be requested to provide some approximate information on your organisation's usual procurement activities. For example, Was the material cost less than what estimates?

| | Strongly Agree (1) | Agree (2) | Neutral (3) | Disagree (4) | Strongly Disagree (5) |
|---|---|---|---|---|---|
| Q9: Material cost of the Supplier is 0 -10% less than the average estimates | o | o | o | o | o |
| Q10: Transportation cost is less than 10% of material cost | o | o | o | o | o |
| Q11: Incidental cost is less than 10% of material cost | o | o | o | o | o |
| Q12: There is no defective item in the supplied order lot, or it is less than 1% | o | o | o | o | o |
| Q13: Supplier can handle all (100%) of abnormal quality problems arising due to supplied machine/equipment. | o | o | o | o | o |
| Q14: Suppliers have more than one quality certification | o | o | o | o | o |
| Q15: Supplier supplies the material on the scheduled date or a delay of a maximum of 3 days. | o | o | o | o | o |
| Q16: Supplier supplies the material on the scheduled date or supply maximum of three days earlier. | o | o | o | o | o |
| Q17: Lead time of Supplier is less than one week | o | o | o | o | o |
| Q18 The Supplier resolves 100% of complaints | o | o | o | o | o |
| Q19: After-sales services are very reliable, and response time is very small (less than 24 h) | o | o | o | o | o |
| Q20: The Supplier has proper infrastructure for research and development work | o | o | o | o | o |
| Q21: Supplier has more than one patent registered. | o | o | o | o | o |
| Q22: Supplier has complete involvement (more than 50%) in collaborating between Supplier and company for new technology/product development | o | o | o | o | o |

Block three (Questions 23 -36) will request your valuable opinion on the impact of having organisational BDAC on healthcare supply chain sustainability.

| | Strongly Agree (1) | Agree (2) | Neutral (3) | Disagree (4) | Strongly Disagree (5) |
|---|---|---|---|---|---|
| Q23: We have a decrease in the cost of material purchased | o | o | o | o | o |
| Q24: We have a decrease in the cost of energy consumption | o | o | o | o | o |
| Q25: We have a decrease in fee for waste discharge | o | o | o | o | o |
| Q26: We have an improvement in return on investment | o | o | o | o | o |
| Q27: We have a reduction in air emission | o | o | o | o | o |
| Q28: We have a reduction in waste (water and/or solid) | o | o | o | o | o |
| Q29: We have a decrease in consumption of hazardous/harmful/toxic materials | o | o | o | o | o |
| Q30: We have a decrease in the frequency of environmental accidents | o | o | o | o | o |
| Q31: We have an increase in energy saved due to conservation and efficiency improvements | o | o | o | o | o |
| Q32: We have an improvement in overall stakeholder welfare or betterment | o | o | o | o | o |
| Q33: We have an improvement in community health and service | o | o | o | o | o |
| Q34: We have a reduction in environmental impacts and risks to the general public | o | o | o | o | o |
| Q35: We have an improvement in occupational health and safety of employees | o | o | o | o | o |
| Q36: We have improved awareness and protection of the claims and rights of people in | o | o | o | o | o |

Q Do you have any suggestions regarding the impact of BDAC on the sustainability of the healthcare supply chain and the mediating role of procurement optimisation?

_____

**Appendix C: Letter requesting participation in the survey**

**Invitation Letter**

Dear XXX

I am writing to you seeking your kind assistance with my research project, which will investigate the impact of Big Data Analytics Capabilities on the Sustainability Performance of Healthcare Supply Chain and the mediating role of public procurement optimisation.

There are no right or wrong answers. Your valuable option only matters. Your participation will contribute to a better understanding of the impact of BDAC on supply chain sustainability. The survey should not take more than ten minutes.

The survey comprises three sections. I have provided a brief description in each section to help the participant understand the contextual meaning of different metrics. You are invited to participate by following the link <> or copying the URL <> and pasting it into your web browser. Your participation and opinion will be highly confidential, and appropriate sensitivity will be ensured.

On behalf of the research team, I would like to thank you for supporting our research in general and my PhD project in particular.

Yours Sincerely,

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---------- This study has been approved by the UTS Human Research Ethics Committee (approval number UTS HREC REF NO. ETH21-5833). Further information on the study, including privacy and confidentiality details, is available in the Participant Information Sheet.

To unsubscribe: <an opt-out link provided>

**First Follow Up Letter**

Dear XXX

I hope this message finds you well. I sent you an invitation to participate in PhD research survey ten days ago. Even if you are not actively engaged in big data projects, your opinion still matters in this project. The project requires opinions from a diverse research poll. I request your kind assistance with my research project, which will investigate the impact of Big Data Analytics Capabilities on the Sustainability Performance of Healthcare Supply Chain and the mediating role of public procurement optimisation. Please disregard this email if you have already filled out the survey. Thank you!

There are no right or wrong answers. Your valuable option only matters. Your participation will contribute to a better understanding of the impact of BDAC on supply chain sustainability. The survey should not take more than ten minutes. If you have not yet looked into the survey, please participate by following the link <> or copying the URL <> and pasting it into your web browser. Your participation and opinion will be highly confidential, and appropriate sensitivity will be ensured.

On behalf of the research team, I would like to thank you for supporting our research in general and my PhD project in particular.

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To unsubscribe: <an opt-out link provided>

**Second and Third Follow Up Letter**

Dear XXX

I sent you an invitation to participate in PhD research survey earlier this month. I understand how busy things can get nowadays. May I request your kind assistance with my research project, which will investigate the impact of Big Data Analytics Capabilities on the Sustainability Performance of the Healthcare Supply Chain and the mediating role of public procurement optimisation? Even if you are not actively engaged in big data projects, your opinion still matters in this project. The project requires opinions from a diverse research poll. Please disregard this email if you have already filled out the survey. Thank you!

There are no right or wrong answers. Your valuable option only matters. Your participation will contribute to a better understanding of the impact of BDAC on supply chain sustainability. The survey should not take more than ten minutes. If you have not yet looked into the survey, please participate by following the link <> or copying the URL <> and pasting it into your web browser. Your participation and opinion will be highly confidential, and appropriate sensitivity will be ensured.

On behalf of the research team, I would like to thank you for supporting our research in general and my PhD project in particular.

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**Appendix D: Participant Information Sheet**

**Research Project:** Role of Big Data Analytics Capabilities Towards Sustainability Performance of Healthcare Supply Chain: Investigating the Mediating Role of Public Procurement Optimisation

**Background:** Big Data Analytics Capabilities are not considered more effective organisational capabilities in pulling useful business insights from a pile of unstructured data. However, research shows that just having BDAC does not guarantee a positive outcome. On the other hand, the same BDAC is not applicable for each context. My PhD project is the first of its kind to explore the role of BDAC on the Sustainability performance of healthcare supply chains in a developing country. The study will also explore the mediating role of public procurement optimisation in BDAC and sustainability performance.

**Privacy and Confidentiality:** While your cooperation in completing the questionnaire is valued, your participation is voluntary. It is important to note that the results from this survey will be used only in an aggregated form. Therefore, your anonymity and the confidentiality of your responses are assured. The completed questionnaire will be securely stored, and the only people who have access to the details of the questionnaires are the researchers and UTS.

**Nature and Extent of Your Participation:** The questionnaire includes questions seeking information about.

a. Analytics tools and methods you or your organisation use
b. General skills and big data-related domain knowledge
c. Managing context of organisational data-related project
d. The current state of procurement and sourcing
e. Organisational sustainability attributes.
f. Demographic information about you and your organisation

Your decision to complete and submit the questionnaire is taken as consent that you have read the information on this information sheet and that you understand the procedures, that your questions have been answered to your satisfaction, that you understand that you do not have to answer any question and that you have voluntarily chosen to participate in this study. Should you have any queries regarding the project or questionnaire, please feel free to contact the main researcher or co-researchers as mentioned in the cover sheet/email invitation.

**Ethics and Complaints:** The UTS Human Research Ethics Committee has approved this study. If you have any complaints or reservations about any aspect of your participation in this research that you cannot resolve with the researcher, you may contact the Ethics Committee through the Research Ethics Secretariat (phone: +61 2 9514 9772, Research. Ethics@uts.edu.au). Any complaint you make will be treated in confidence and investigated fully, and you will be informed of the outcome.

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