Review

Business Intelligence and Business Value in Organisations: A Systematic Literature Review

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Abstract: Organisations must derive adequate business value (BV) from Business Intelligence (BI) adoption to retain their profitability and long-term sustainability. Yet, the nuances that define the realisation of BV from BI are still not understood by many organisations that have adopted BI. This paper aims to foster a deeper understanding of the relationship between Business Intelligence (BI) and business value (BV) by focusing on the theories that have been used, the critical factors of BV derivation, the inhibitors of BV, and the different forms of BV. To do this, a systematic literature review (SLR) methodology was adopted. Articles were retrieved from three scholarly databases, namely Google Scholar, Scopus, and Science Direct, based on relevant search strings. Inclusion and exclusion criteria were applied to select ninety-three (93) papers as the primary studies. We found that the most used theoretical frameworks in studies on BI and BV are the Resource-Based View (RBV), Dynamic Capabilities Theory (DCT), Technology-Organisation-Environment (TOE), and Contingency Theory (CON). The most acknowledged critical factors of BV are skilled human capital, BI Infrastructure, data quality, BI application and usage/data culture, BI alignment with organisational goals, and top management support. The most acclaimed inhibitors of BV are data quality and handling, data security and protection, lack of BI Infrastructure, and lack of skilled human resource capital, while customer intelligence is the most acknowledged form of BV. So far, many theories that are relevant to BI and BV, critical factors, inhibitors, and forms of BV were marginally mentioned in the literature, requiring more investigations. The study reveals opportunities for future research that can be explored to gain a deeper understanding of the issues of BV derivation from BI. It also offers useful insights for adopters of BI, BI researchers, and BI practitioners.

Keywords: business intelligence; business analytics; big data analytics; business value; firm performance

1. Introduction

Business Intelligence (BI) is heavily documented in the literature as a tool capable of aiding business progression through better decision-making processes and subsequently firm performance and business value (BV) [1,2]. The contemporary business environment has become dynamic and heavily competitive; therefore, business organisations must make accurate decisions to ensure continuous profitability and sustainability in the long term [3,4]. Thus, strategic information and market-related intelligence have become imperative for all organisations wishing to retain profitability, relevance, and sustainability which has led to an increased focus on Business Intelligence (BI) [3]. BI enables the crunching and analysis of immense volumes of organisational data to generate strategic information. This is conducted through identifying variable correlations and discovering patterns that are capable of providing enlightened organisational decisions which can vastly improve organisational strategic decision making [4,5].

Both practitioners and researchers alike show interest in BI as it has become synonymous with firm performance, at least in theory [1,4,6]. The reality is much different; the business value (BV) realised from the implementation of BI remains uncertain as some

adopters of BI indicate little value from BI implementation [7–10]. The source of the disparity is centred on the misconception of how value is generated and realized [1,6,11–13].

For the sake of this study, BI is defined as "processes and systems (such as data warehouses, data marts, analytical tools such as reporting tools, ad hoc analytics and OLAP, in-memory analytics, planning, alerts, forecasts, scorecards and data mining) that transform raw data into meaningful and useful information and enable an effective, systematic and purposeful analysis of an organisation and its competitive environment" [2]. The definition acknowledges the relationship between Big Data, Business Analytics, Data warehouses, and Business Intelligence as interrelated aspects in information systems, sometimes interchangeably adopted to mean the same [14]. BV is identified as "the transactional, informational and strategic benefits" realised from the adoption of BI [15]. Business value (BV) and firm performance (FP) will interchangeably be used as they are related and are used in some instances in the literature as such [16].

Previous research efforts managed to establish the link between BI and BV by analysing business capabilities and operational strategic business value [11,16]. However, little is known about how BV is created as most of the papers in the literature concentrate on the technical aspects of BI [11]. Furthermore, despite the close relationship that Information Technology (IT) and BV share, previous studies on BV in IT do not explain the relationship between BV and BI, as BI possesses distinctive characteristics such as implementations strategies and usage unique to only BI and not IT [16].

This paper adopts a systematic literature review approach to investigate the relationship between BI and the creation of BV in organisations. A systematic literature review provides a basis to deduce a cohesive narration of the state of the literature on a particular topic which in this case is to foster a deeper understanding of the relationship between BI adoption within organisations and BV creation from BI within organisations [17].

The main aim is to foster a comprehensive understanding of BV derivation from BI based on the theories and theoretical frameworks that have been used as lenses to examine BV derivation from BI, the critical factors of BI adoption, the inhibitors of BV derivation, and the various forms of BV. In most papers on BV, an underlining theory is present which dictates the perspective from which BV is viewed [18–20]. For instance, in some papers where BV is established through the examination of utilised resources, a Resource-Based View (RBV) theory is occasionally employed as a lens to understand the creation of BV [21,22].

The critical factors of BI adoption are well documented in the literature [23–25]; however, the critical elements that aid organisations across the world to realise BV from BI are shallowly discussed. These critical factors are paramount in understanding how BV is derived from BI. Moreover, it is essential to identify the factors that inhibit the realisation of BV from BI adoption and the various forms of BV.

The uniqueness of this systematic review paper stems from the composition of the four research questions that are investigated and the specific emphasis on the relationship between BI adoption and BV in terms of theories that have been applied to understand BV derivation from BI, the factors influencing the derivation of BV from BI, the hindrances to the realisation of BV from BI, and the different forms of BV. To the best of our knowledge, no previous study has looked at the relationship between BI and BV from these same aspects to offer a comprehensive perspective.

This paper is significant for both researchers and practitioners as it offers a comprehensive view of what has been conducted so far in the literature on the relationship between BV and BI, but also seeks to reveal existing gaps that may require further research explorations. This will enable adopters of BI to achieve a good return on investments and further increase the level of success of BI [12,26]. The paper will foster a deeper understanding of the issues of BV creation from BI in organisations and the advancement of future research on BV.

The rest of the paper is structured as follows: Section 2 presents the background and related work on BI adoption and BV, while Section 3 discusses the methodology that was adopted for the study. Section 4 presents the results, with the discussion in Section 5.

Section 6 presents the limitations of the study, while the paper is concluded in Section 7 with a summary and the outlook of future work.

2. Background

2.1. Business Intelligence (BI)

BI has evolved over the years since its introduction in the 1990s where it was mostly adopted in IT and business societies where a regular set of data matrixes was employed to generate information and devise future planning. In the early 2000s, BI evolved into a more analytical centric tool, which was identified in the literature as Business Analytics (BA). BA adopts a more liberal stance with regards to datasets employed to gain new information and conjure meaning from organisational performances through a focus on statistical and mathematical insights [27]. In essence, BI focussed on reporting, while BA emphasises both reporting and prediction of the future. The latest term that evolved from BI and BA is Big Data or Big Data Analytics which represents larger volumes and complex sets of data requiring dedicated tools to synthesise information while still upholding the same emphasis on reporting and predictive analytics [28].

2.2. Business Value in BI

Business Value embodies the set of benefits and advantages that are derived from BI adoption in organisations. According to [26,29,30], the most important question is not how much money should be spent on data analytics, but how much value is derived from data analytics. Based on the finance theory, a good motivation for continuous investment in data analytics is when the literal amount of value that is generated exceeds the cost. This perspective indicates the significance of BV in BI adoption.

BI Capabilities

Research in the past indicates a uniformity on the rhetoric of BI Capabilities and their influence on realising BV [16,31,32]. Stemming from the Resource-Based View (RBV) theory, BI Capabilities are deemed essential for superior BV especially if the BI Capabilities in question share an interrelated relationship with other BI Capabilities to achieve an analytical capability; however, this has yet to be achieved [33]. Ref. [18] affirm that dynamic capabilities alone do not guarantee BV, but the inclusion and use of operational capabilities also matter. Furthermore, Ref. [16] argue that there are differences in the BV processes for various technologies; therefore, each BI case must be treated independently.

BI Capabilities are defined as organisational abilities based on the technology used to aid the synthesis of large-volume and high-velocity data, as well as various forms of data sets [34]. The role played by dynamic capability within value creation is explained by [6] who observed that dynamic capability enables practitioners to make better decisions to create value. With the aid of the RBV theory, the authors indicate that with the use of dynamic capabilities inspired by quality BI and organisational structure, firm performance (FP) and business value (BV) can be achieved. Additionally, the authors recognised the significance of the decision-makers themselves within the process of value creation.

BI Capabilities have been acknowledged as suitable to provide agility to organisations that use the approach to value creation [12]. Ref. [31] identify three forms of BI-related capabilities, and they include BI Capabilities, BI Innovation Infrastructure Capability, BI Process Capability, and BI Integration Capability, as all are integral for the internet capability network. Refs. [5,35] present a framework based on Big Data Capabilities which stems from the organisational information processing system where Big Data processing requirements and Big Data processing capabilities are incorporated together to realise BV. Value chains can be used to establish value creations. According to [36], through the analysis of descriptive, predictive, and prescriptive analytics, organisations can apply a value chain where BI Capabilities are identified to create BV subsequently.

3. Related Work

This section presents an overview of systematic review papers that focussed on the topic of BI and BV.

Ref. [10] investigated the issue of Business Analytics assimilation within organisations to achieve competitive advantage through organisation absorption capacity. The authors discovered that Business Analytics Capability (BAC) has a direct and indirect influence on Business Analytics Assimilation (BAA) with a strong mediating role from the organisational capabilities. Furthermore, a cross-cultural environment affects the levels of BA adoption. Ref. [37] conducted a systematic literature review (SLR) to shed light on BI-related activities such as BI issues and challenges, adoption, utilisation, and success since there is the uncertainty of the realisation of the benefits of BI. From the 111 papers that were examined in the study, the authors discovered that 28% were dedicated to BI adoption, and 38% were aimed at BI assimilation. A total of 28 theories were identified as being used within BI research where DeLone and McLean's IS success model, the technology acceptance model, and the diffusion of innovation theory were the most prominent. They also observed that the three categories of factors necessary for BI success are organisational perspective (e.g., organisational goals, strategies, and plans), information systems (IS) perspective elements (e.g., IT infrastructure and dashboard presentation), and user perspectives (which include human resource factors). According to the authors, the challenges of BI adoption included user acceptance, lack of BI support, insufficient communication between staff and IT department, and insufficient service quality.

Moreover, Ref. [38] explore the influence of BI on small- to medium-sized enterprises, and their finding indicated that data volumes are of critical importance to smaller firms where they are in limited supply, and equally important are critical and strategic data that can add a competitive advantage. Moreover, smaller firms struggle to acquire skilled personnel to produce and present information to management, as it is costly for small organisations to possess personnel of such calibre on their team. Moreover, the members of management who are supposed to use the information are not well equipped to apply the information gathered.

Ref. [16] analysed the value creation of multiple case studies through the assessment of the dispensation of organisational resources, particularly BI-related resources, and the financial performance measurements that were achieved. Ref. [39], through the analysis of multiple case studies, tried to identify the assets and organisational capabilities that are required to achieve business value. The paper identifies analytical tool assets, business capabilities, analytical value enhancers, and organisational levels as key aspects of business value realisation. Ref. [26] investigated the nuances of how value is generated through the application of the DELTA theory. The authors proposed a value realisation model, where factors such as ongoing business analytics improvements, such as the functional fit to BI tools, readily available BI data, analytical people, and overcoming organisational inertia, which subsequently result in organisational benefits from analytical use, are incorporated, from the perspective of senior management. Additionally, the model also incorporates analytical leadership, enterprise-wide analytics orientation, well-chosen targets, and the extent to which evidence-based decision making is embedded in the "DNA" of the organisation.

Ref. [1] reviews the previous literature on the BI and BV by interrogating what has been recorded in the BI literature, reassessing the level of understanding of the available literature, and what is lacking in the literature with regards to business value realisation. The paper discovered that BI-assets-related papers constituted the highest contribution to BI research, with BI impacts and BI management also contributing significantly. The least explored areas of BI include non-bi-investment realms, country factors, competitive dynamics, and competitive positions.

Ref. [40] tried to establish key components for BI adoption and usages. Based on the Technology-Organisation-Environment (TOE) framework, the author identified factors that are imperative for BI adoption, which are data-related infrastructure capabilities, data management challenges, top management support, talent management, external market

influence, and regulatory compliance. Ref. [41], in their review, concluded that BI consists of four stages of diffusion, which include BI adoption, BI implementation, BI use, and impact of use. They observed that these four stages are crucial so that a proper assessment of the BI evolutionary process can be better comprehended. They also observed that a great emphasis has been placed on BI adoption where most papers employed quantitative methodologies. The authors also noted that after adoption, the next level of focus is the application of BI where most papers have conducted cross-sectional research from single-country cases. The impacts of BI on organisations are also explored through the use of examples that indirectly demonstrate the potential benefits of Business Intelligence and analytics. However, according to the authors, empirical investigations on the realisation of the benefits of BI are still very few or rare.

A summary of the emphasis of the previous papers on the issue of BI and BV is presented in Table 1. It can be seen that thus far no study focussed on presenting an understanding of the relationship between BI and BV as conceived in this study, particularly from the perspective of theories that have been applied, key factors that aid BV creation, hindrances to BV derivation from BI adoption, and the different forms of BV that exist.

Table 1. Summary of related work.

Paper	Main Theme/Objective	Type of Paper	Classification
[10]	Business analytics assimilation (BAA) through organisational Absorptive capacity (AC) in organisations to achieve competitive advantage	Empirical paper	BI adoption
[37]	BI adoption, use, or success (AUS); Theories/frameworks/models for BI AUS; Key factors of BI AUS; Challenges of BI AUS in organisations; and Knowledge gaps in BI AUS research	SLR	BI adoption, challenges, utilisation, and success
[38]	BI application to SMEs	SLR	BI for competitive advantage among SMEs
[16]	Understanding the contribution of business analytics to business value creation in firms	A comparative case study	Business Value Creation
[39]	Impact of BDA on operations management in the manufacturing sector	Comparative case study	Business Value Creation
[26]	Creation of a business analytics success model (BASM) that explains how business analytics contributes to business value Preliminary assessment of the BASM	Review	Business Value Creation
[1]	An examination of research studies (between 2000 and 2015) that were conducted on the processes of organisations obtaining value from BI systems The focus was on what do we know, how well do we know, and what do we need to know about the processes of organisations obtaining business value from BI systems?	SLR	Business Value Creation
[40]	Factors that influence Business Intelligence and analytics usage extent	Empirical paper	BI Adoption
[41]	Mapping of BI&A research on its several diffusion stages of adoption, implementation, use and impacts of the use	Systematic mapping study	Diffusion stages of BI&A

Compared to empirical papers, comparative case studies, or descriptive reviews that draw their conclusions from a limited scope, a systematic literature review (SLR) uses a structured and methodical approach to answer specific research questions of interest. So far, two recent systematic reviews that deal with the subject of BI and BV were found. The paper by [37] did not focus mainly on understanding the relationship between BI and BV but on the more general aspects of BI adoption, use, and success (AUS). Thus, it did not delve deeply into providing an understanding of the relationship between BI and BV.

Similarly, Ref. [1] examined the research studies between 2000 and 2015 that focussed on how BV is obtained from BI by organisations. However, the focus was to highlight what is already known, the depth of what is known, and what more still needs to be known on how BV is obtained from BI. The study did not delve into the analysis of the theories and theoretical frameworks that have been used to examine the relationship between BI and BV, and the different forms of BV from BI as conceived in this study. Specifically, based on the four research questions that we selected, this study offers a different perspective compared to other systematic reviews because it enables the identification of:

- The theories that have been used as lenses to understand the relationship between BI and BV (RQ1);
- The key factors for the derivation of BV from BI (RQ2);
- The inhibitors of BI and BV (RQ3); and
- The different forms of BV identified by authors that have studied the issue of BV creation from BI (RQ4).

4. Methods

The adopted methodology used for this systematic literature review was inspired by the work of [38,42,43].

4.1. Research Questions

This paper aims to foster a deeper understanding of the relationship between BV realisation and BI adoption. This aim stimulated the following research questions:

1. Which theories have been used by researchers to understand the relationship between BI and BV?
2. What are the critical factors that aid the derivation of BV from BI adoption in organisations?
3. What are the inhibitors of BV from BI adoption in organisations?
4. What are the different forms of business value that have been reported from BI adoption in organisations?

Research Justification

Based on Table 1, which presents an analysis of related work, it can be seen that efforts have been made to understand adequately how BV is achieved from BI. The uniqueness of this paper stems from its main focus on the 4 research questions that were selected to understand the relationships that exist between BI adoption and BV creation. To the best of our knowledge, no previous review paper has attempted to identify critically and methodically (i) the theories that have been used to understand the relationship between BI and BV; (ii) the key factors that are important for the derivation of BV from BI; (iii) the inhibitors of BV from BI adoption in organisations; and (iv) the different forms of BV that have been associated with BI adoption. This kind of detailed and targeted perspective on the relationship between BI and BV will be valuable for BI researchers, BI practitioners, and organisations that have adopted BI.

4.2. Search String

An effective search string should have three main parts which include intervention, comparison, and outcome [42]. The relevant papers for this study were acquired through the use of search strings composed of keywords that were based on the research questions outlined above, and the application of relevant inclusion and exclusion criteria. The search strings adopted include "Business Intelligence" OR "Business Analytics" OR "Business Intelligence & Analytics" OR "Big Data Analytics" AND "Business Value" OR "Firm Performance".

An overview of the process that was adopted for the execution of this systematic literature review is shown in Figure 1.
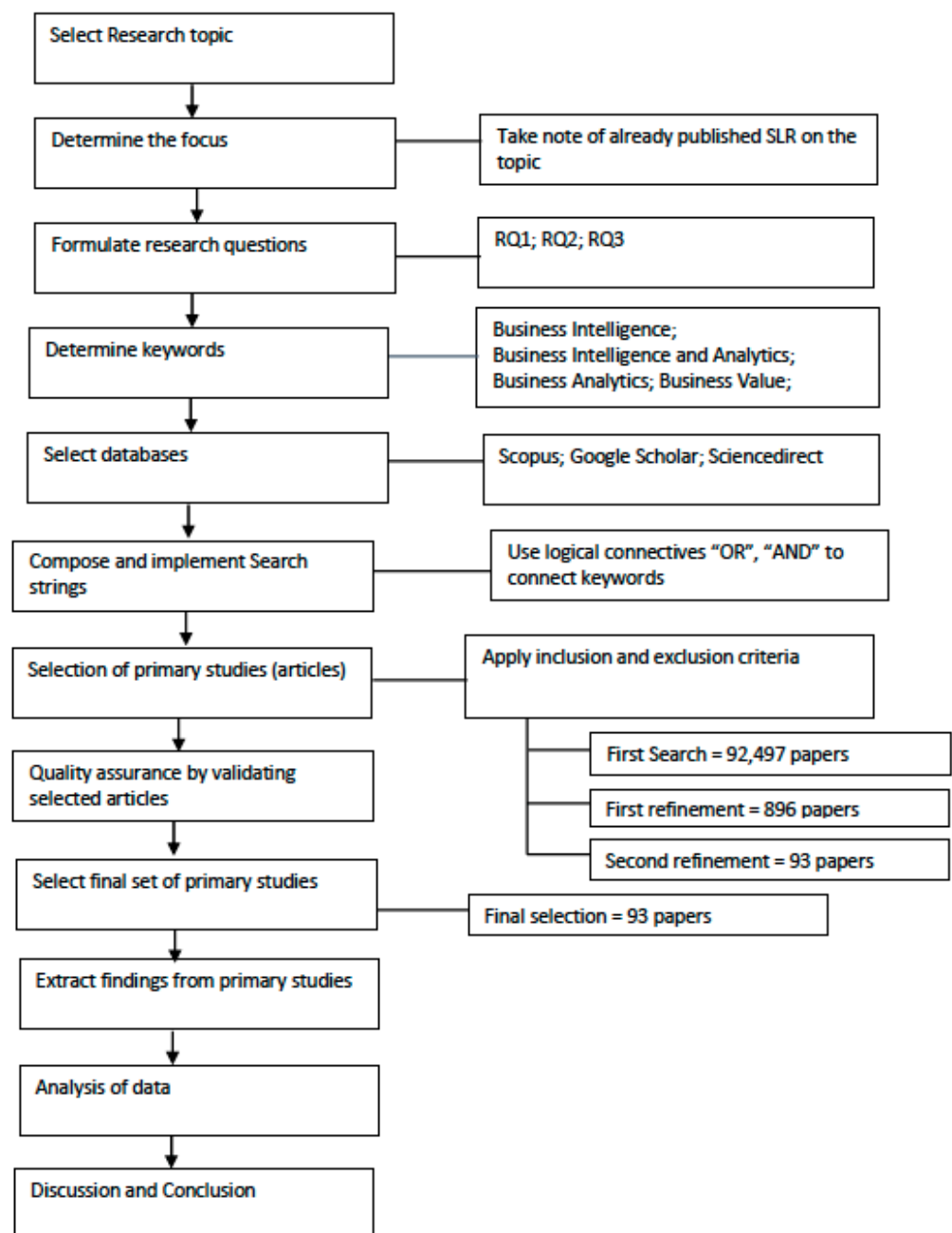
Figure 1. Overview of the process adopted for the SLR.

4.3. Data Sources

To gain access to relevant papers, it is essential to consult standard databases that have a huge collection of credible published papers. The databases consulted for the study are Google Scholar, Scopus, and Science Direct. The description of each of these is presented in Table 2.

4.4. Data Retrieval

By adopting the Boolean "OR" and "AND" terms, the keywords outlined earlier were applied in search operations in Google Scholar, Scopus, and Science Direct databases. The objective of using both "OR "and "AND" was to include BI term alternatives as well as include results with business value and firm performance. The search resulted in a total of ninety-two thousand four hundred and ninety-seven (92,497) journal and conference papers.

The resulting list was pruned down by selecting journal and conference papers from the list which include the keywords outlined above in the title. A total of 896 articles met this criterion.

The list was further refined by eliminating papers that appeared on the list of all three databases or more than one database, which yielded 335 papers. The list of remaining papers was stored in a MS Excel spreadsheet where the details of each paper were outlined including the source of the paper (respective database), search string, author, aim, context, method, result, and critique. Furthermore, the abstracts of the papers were reviewed, and papers that were not relevant to the study areas were discarded. A two-state criteria system was applied based on the level of relevance to the subject area, namely, "relevant" and "not relevant". Inclusion and exclusion criteria were applied to determine the level of relevance of each paper which led to ninety-three (93) papers being classified as relevant, while 242 papers were deemed irrelevant to the study and discarded (see Table 3). The papers were then associated with the specific research question(s), with some papers found relevant to multiple research questions as shown in Table 1.

Table 2. Overview of Database Sources used for the study.

Database	Description
Google Scholar	Google Scholar is a web-based database containing roughly 389 million full-text documents from various authors and disciplines on scholarly literature. Introduced in November 2014, the database encompasses online peer-reviewed journal papers, books, theses, dissertations, abstracts, patents, court reports, and conference papers.
Scopus	Launched in March 1997, over 12 million pieces of science and medical content from 3500 peer-reviewed academic journals are indexed in Scopus.
Science Direct	Concentrated on peer-reviewed academic journal format coverage, Science Direct boasts 12 million pieces of content from 3500 academic peer-reviewed journals and 34,000 electronic books.

Table 3. Result of Data Retrieval and Refinement.

	Google Scholar	Scopus	Science Direct	Total
Number of papers	90,600	525	1372	92,497
	First Refinement:			
Number of papers	298	203	395	896
	Second Refinement:			
Number of papers	50	28	15	93

4.4.1. Inclusion Criteria

The papers selected for this study needed to cover the concepts of BV, FP, and BI, particularly with regards to value creation processes. Furthermore, the publications must be peer-reviewed journals or conferences to ensure the authenticity and accuracy of information.

4.4.2. Exclusion Criteria

The exclusion criteria for papers that were deemed irrelevant include the following: (i) papers not written in English; (ii) papers that did not focus on BI and BV or BI and firm performance based on the abstract, title, or introduction so that the research questions could be answered; and (iii) papers before 2009 were disregarded due to the need for relevance to the current trends on the topic.

4.4.3. Quality Assurance

Quality assurance was performed to ensure that only the relevant papers were selected as the primary studies. To do this, the set of papers selected by the first author after applying

the inclusion and exclusion criteria was cross-checked by the second author to ensure that valid choices were made in the selection of papers. During the process, it was discovered that 1 paper that used the Diffusion of Innovation (DOI) theory to study the issue of BV in BI adoption was omitted from the final selection although it was retrieved as part of the initial selection. The paper was re-introduced into the pool of selected final papers. Thus, a total of 93 papers were selected as the primary studies for the systematic review.

5. Results

The findings for the four research questions are outlined in the following sections.

5.1. Which Theories Have Been Used by Researchers to Understand the Relationship between BI BV?

Theories play a pivotal role in value realisation as they determine the measures of BV from BI adoption. As such, understanding the theories that have been adopted in the literature to study business value is a good stepping stone to comprehend the nuances of value creation. The numerous theories adopted in BV studies originate from various corners of learning such as strategic management, microeconomics, industrial-organisational, socio-political, organisational-behavioural, and business-strategical spectrums [16]. We found that the commonly adopted theories consist of the popular perspectives of Resource-Based View (RBV), Dynamic Capability (DC), Critical Value Factor, Technology Organisation and Environment (TOE), IS Success theory, DeLone and McLean, Knowledge Management (KM), and DELTA [12,21,31,34,44–46]. Some of the theories that were employed to study business value creation are presented as follows:

1. Resource-Based View Theory (RBV): Originating from strategic management, RBV stipulates that resources should be strategic; they need to be Valuable, Rare, Inimitable, and Non-substitutable (VRIN) [17].
2. Dynamic Capability Theory (DCT): Dynamic Capability theory focusses on organisational resources, as with RBV, where resources are viewed as organisational capabilities and are identified as instrumental to value realisation through BI through the perceived agility it provides to organisations to adapt to change [36,47].
3. Sense Seize and Transform (SST): "Sense" represents possible opportunities and threats a business can incur [47]. "Seize" refers to the universal agreement within an organisation on the possible action applicable to capitalise on areas "sensed" as well as the deployment of resources to facilitate the capitalisation of the sensed areas. "Transformation" entails the affirmative action taken by an organisation based on the areas "sensed" and the processes "seized" which can include process reengineering, business model adjustments, and realignment of assets promptly [12].
4. IS Success Theory (IST): According to [48], IS Success theory is based on six (6) interdependent pillars, namely system quality, information quality, user satisfaction, use, and individual and organisational impact.
5. DELTA Model: The theory was revised in previous years to include more attributes and is now referred to as DELTTA, embodying Data, Enterprise, Leader, Target, Technology, and Analysts [45].
6. Business Process Theory (BPT): The theory is inspired by Total Quality Management (TQM) and Business Process Re-engineering (BPR) processes where effectiveness and efficiency are expected outcomes. The TQM and BPR are fundamentally orientated toward achieving a favourable outcome in the form of firm performance and/or BV. As such, the application of the Business Processes theory allows for the redesign of organisational processes to assimilate BI and achieve firm performance [49].
7. Contingency Theory (CON): The contingency theory is based on a flexible perspective of how an organisation should be run. The premise of the theory states that there is no best way to run an organisation; however, management is expected to adjust and reform according to the internal and external situations [50,51].
8. The McKinsey 7S's framework (TMF): The theory is based on an interdependent network of factors where a change in any one of the factors must result in the change

of the other factors as well. The theory detects and analyses the effectiveness of an organisation's financial performance to achieve set goals. The factors in question include the strategy, structure, systems, staff, skills, style, and shared values [52].

9. Knowledge-Based View (KBV): The theory is of the notion that knowledge is an organisation's most important resource and as such must be strategically applied to realise firm performance [53].

10. Data, Information, Knowledge, and Wisdom (DIKW): The DIKW model is centred on four factors, namely Data, Intelligence, Knowledge, and Wisdom, to aid in value creation through redesigning organisational processes and routines [54].

11. Balanced Scorecard (BC): Financial measures of firm performance are important to an organisation; however, the Balanced Scorecard is of the notion that they alone do not present a true reflection of organisational success; therefore, it is imperative also to consider non-financial means such as customers, internal business processes, and learning and growth development [55].

12. Systems Theory (ST): Systems theory states that a process or system is made up of interacting subsets which are smaller than the system itself and when combined will form the system [56].

13. Value Theory (VT): Anchored on the perception of value, the value theory seeks to indicate qualities that establish value from BI processes that are occasionally hidden or undiscovered to users [57].

14. Complexity Theory (CT): The theory indicates that various variables randomly interact with each other, and the outcome is not normally predictable [58].

15. Technology Environment Organisation (TOE): The adoption of technology is viewed from three scopes: inclusion of Technology, representing old and new technology the organisation has; Organisation, encompassing the attributes of the organisation such as size, structure, and scope; and Environment, which involves externally influenced factors such as industry competitors, industry size, and the regulatory environment [40,59].

16. Diffusion of Innovation Theory (DOI): The theory examines the adoption of innovation and technology within organisations through the application of a three (3)-step process to realise the associated benefits, namely evaluation (persuasion stage), adoption (decision stage), and use (implementation stage) [60,61].

17. Process Theory (PT): Emphasises the gradual development and change of matter from one form to another through the collaboration of elements facilitating the change, "a recipe" with no predictable outcome [62].

18. Sociomaterialism Theory (SMT): Encompasses the notion "that there is nothing in the world over and above those entities which are postulated by physics (or, of course, those entities which will be postulated by future and more adequate physical theories)" [63].

19. Social Capital Theory (SCT): The theory is anchored on the premise of inter- and intra-organisational sharing of imperative resources such as knowledge, support, and value creation [64].

20. Knowledge-Based Dynamic Capability Theory (KBDC): Extends from the RBV and DC theories with one critical difference, which is the emphasis on knowledge of DC initiatives [64].

21. Configurations Theory (COT): A newly applied collective approach to analyse complex elements to identify patterns and structures through synergetic interactions [65].

The theories listed in Table 4 are the most mentioned and applied in papers that focussed on BV and BI in the literature, while the theories in Table 5 are those that were conservatively applied on the issue of BI and BV. Therefore, both tables do not represent any prioritisation or establish any level of importance of specific theories to the topic of BI and BV but instead indicate the frequency of mention so far in the literature. Additionally, Figure 2 depicts the number of times that specific theories have been employed in BV research.

Table 4. List of papers where specific theories were applied.

Theory	Articles Where the Theory Was Applied	Number of Papers
Resource-Based View (RBV)	[10,15,22,35,61,66–88]	30
Dynamic Capability Theory (DCT)	[11,17,18,21,33,77–80,83,87,89–93]	17
Technology-Organisation-Environment (TOE)	[7,37,40,46,79,81]	6
Contingency Theory (CON)	[64,74,75,83,86,94]	6
Sociomaterialism Theory (SMT)	[72,74,79,88,89]	5
Complexity Theory (CT)	[64,79,90,91]	4
DELTA	[26,45,82]	3
Knowledge-Based View (KBV)	[64,84,93]	3
Data, Information, Knowledge, and Wisdom (DIKW)	[54,94]	2
Balanced Scorecard	[95,96]	2
The McKinsey 7S's Framework (TMF)	[52,97]	2
IS Success Theory (IST)	[15,66]	2
Systems Theory (ST)	[8,98]	2
Diffusion of Innovation (DOI)	[79,81]	2
Process Theory (PT)	[62,99]	2

Table 5. The rest of the other theories, definitions, and paper theories adopted.

Theory	Paper Applied	Number of Papers
Sense Seize and Transform (SST)	[12]	1
Business Process Theory (BPT)	[100]	1
Value Theory (VT)	[100]	1
Social Capital Theory (SCT)	[64]	1
Knowledge-Based Dynamic Capability (KBDC)	[64]	1
Configurations Theory (COT)	[101]	1
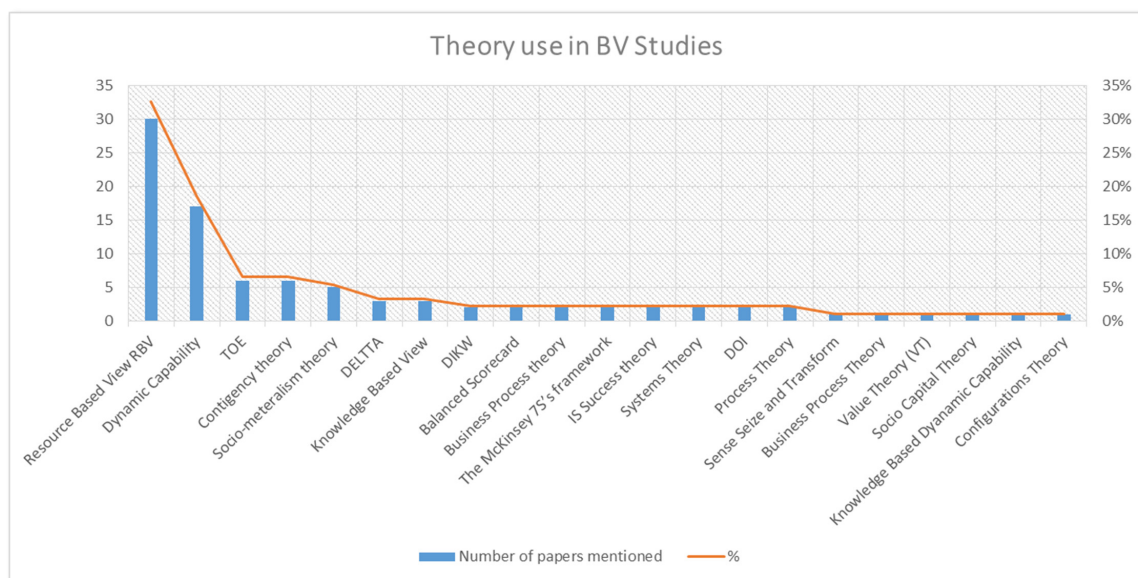
Figure 2. Overview of all the theories mentioned.

5.2. What Are the Critical Factors That Aid the Derivation of BV from BI Adoption in Organisations?

There are varying accounts documented on the critical elements for BV realisation from BI which all depend on various other variables such as organisational industry, size of the organisation, IT capital accessibility, and the degree of influence of external environments on the organisation despite certain similarities to certain degrees [8–10,81,90].

According to [9], there are six (6) core elements instrumental for BV realisation. They include dynamic capabilities which enable an organisation to react better to any external situations whether friendly or hostile [5,12]. An example of the influence of DC on BV can be cited with Amazon where they manage and predict shipping for their clients. Furthermore, DC are also influential within soft spaces of BI applications such as people, where, in recent case studies, some organisations were identified to apply BI on their employees by inserting trackers on the employee name badges so that they can track the social interactions of their staff. By doing so, they managed to discover that employees who take breaks together achieve higher levels of productivity, a practice which later was instituted into the mandate of the organisation [91]. The authors also identified firm agility as another factor, a by-product of DC, where consistent experimentation over time can allow organisations to understand the internal and external environment around them, therefore enabling firm agility [34]. Additionally, there is a need for an alignment between IT infrastructure and the organisation and organisational goals, as the focus is orientated on the attainment of organisational goals through BI, not necessarily the volume of data processed. The data management process must match the direction of the organisation; otherwise, as stated in the DIKW theory, it is just data without "context or interpretation" [102], (p. 7). The role that BI plays within an organisation is also important to the realisation of BV, as how centred it is within the organisational operations and strategic orientation will determine the level of BV success.

Furthermore, for the alignment to take place, management influence and support are contributory to BV success, as top management holds the responsibility to spur the company to employ the necessary philosophy and authority to apply BI into operations and, importantly, reserves the right to distribute company resources [103].

This point subsequently introduces the fifth point of BI usage, as the author shares an example where BI is applied in bet houses where the company analyses customers' transactions to behavioural attributes to predict and market future services to its clients. Finally, environmental influence and volatility represent the eternal forces the business consistently interacts with [9].

Table 6 depicts all the critical factors that were identified to influence the BV of BI as well as the theories that were applied. Moreover, Figure 3 shows the number of sources (papers) that mentioned these critical factors.

Table 6. BV critical factors, theories, and sources.

Critical Factor	Theories Applied	Sources of Mention
Dynamic capabilities	CT, DCT, VT, DIKW, RBV, DCT, COT, KBV	[6,9,12,16,29,39,46,54,57,70,83,85,90,94,95,104–106]
Organisational agility/dynamism	DCT, CT, VT, BPT, CON, KBV	[6,9,57,77,80,83–85,95,96,104,107–109]
BI Infrastructure	DCT, TOE, DOI, RBV	[1–3,5,6,9,12,16,19,26,45,46,69,70,72,77,78,80–83,87,91,96,99,102,104–106,110–113]
BI alignment with organisational goals	DCT, DELTTA, TOE, DOI, RBV, DIKW	[6,9,12,19,26,45,46,72,76,79,88,90,93,94,96,100,102,104,107,111,112,114,115]
Clear organisational goals	DCT, DELTTA	[2,26,45,82,90,97,112,116]
Top management support	DCT, DELTTA, TOE, DOI, RBV, KBV	[1,3,9,12,26,40,45,46,52,78,80,81,83,84,87–89,91,94,97,105,106]
Data quality and internal information sharing	DCT, DELTTA, RBV, VT, DIKW, BPT, VT, CON, KBV, IST	[5,6,9,15,19,26,45,54,57,72,75,80–82,84,90,91,94,96,100,104–106,110,112,113,115,117–119]
BI application and usage/Data Culture	DCT, CT, RBV, BPT, VT, CON	[5,9,10,16,19,26,29,33,70,79,83,84,88,90,93–95,104,108,109,113]
Environmental factors	DCT, TOE, DOI, CON	[9,40,64,68,86,88]

Table 6. *Cont.*

| Critical Factor	Theories Applied	Sources of Mention
Skilled human capital	DELTTA, RBV, BPT, VT, CON, TMF	[1,5,10,12,21,26,33,40,45,46,69,70,72,77,78,80–84,87,88,90,93,100,102,104,108,115,120,121]
Procedural practises	DCT, CT	[2,5,10,26,69,77,84,94–96,108,118]
Governance regulations	TOE, DOI, SCT	[1,3,21,64,106]
BI adoption process	TOE, DOI	[3,16,112]
Competitive pressure	TOE, DOI	[1,3,19,85,99]
Perceived benefits	TOE, DOI, DCT	[2,3,6,19,26,46,83,92,109,115,118,121]
Organisational readiness	TOE, DOI, RBV, DC, CT, VT, CON	[2,3,16,83,93,104]
BI Investment	RBV, DIKW, PT, DCT	[1,62,68,105,111,112]
Planning	RBV, SMT, TMF	[12,88,97]
Organising	RBV, SMT	[88]
BI-influenced Decision Making	SCT, KBDC	[64]
Latency effect	RBV	[1]
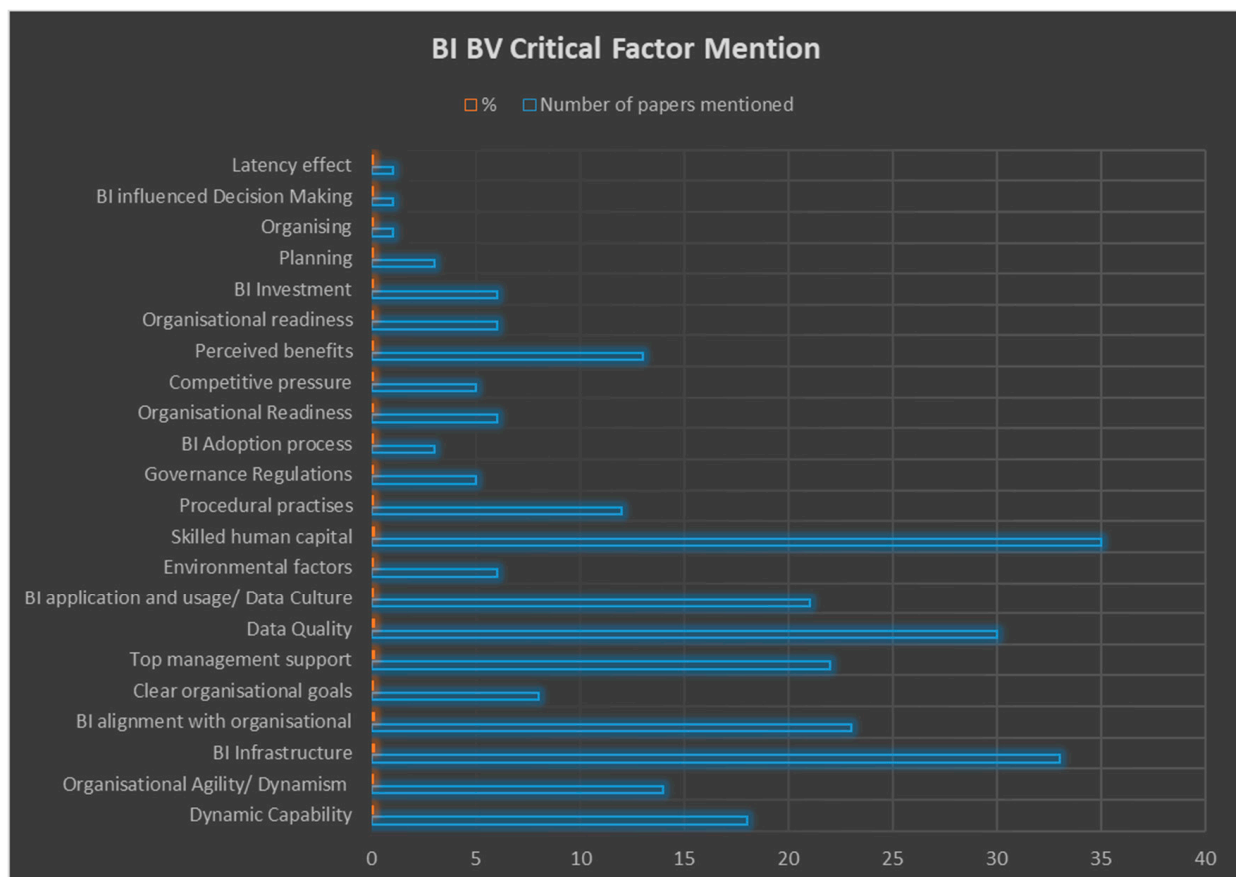
Figure 3. BI BV Critical Factors Mentioned.

The alignment among the various theories and identified critical factors is shown in Table 7.

Table 7. Alignment among theories on critical factors.

Critical Factor	DCT	CT	VT	DIKW	RBV	TOE	DELTTA	DOI	PT	SMT	SCT	KBDC	COT	BPT	CON	BSC	SST	TMF	IST	ST	KBV	Total
Dynamic Capabilities	✓	✓	✓	✓									✓	✓							✓	7
Organisational Agility/Dynamism	✓	✓	✓		✓									✓							✓	6
BI Infrastructure	✓				✓	✓		✓							✓							5
BI alignment with organisational goals	✓		✓		✓	✓	✓	✓			✓											7
Clear organisational goals	✓						✓															2
Top management support	✓				✓	✓	✓	✓							✓						✓	7
Data Quality	✓		✓	✓	✓		✓								✓	✓	✓		✓		✓	10
BI application and usage/Data Culture	✓	✓			✓										✓							4
Environmental factors	✓					✓		✓							✓							4
Skilled human capital					✓		✓											✓				4
Procedural practices	✓				✓																	2
Governance Regulations						✓		✓			✓				✓							4
BI Adoption process						✓		✓														2
Organisational Readiness						✓		✓						✓	✓							4
Competitive pressure		✓				✓		✓														3
Perceived benefits	✓					✓		✓														3
Organisational readiness						✓		✓														2
BI Investment				✓	✓				✓													3
Planning					✓					✓							✓	✓				3
Organising					✓					✓												2
BI-influenced Decision Making					✓						✓	✓										4
Latency effect					✓																	1

5.3. What Are the Inhibitors of BV from BI Adoption in Organisations?

It is imperative to understand the inhibitors to BV realisation so that these inhibitors can be further investigated to improve BV efficiency from BI amongst practitioners.

BI heavily depends on data which are the core resource that enables organisations to perform data analytics. The protection of data is still an area of concern for some organisations that find advanced data security systems expensive [79]. As such, these organisations are reluctant to adopt BI and despite the hysteria around BI and its benefits. This is especially true for small enterprises where resources, particularly financial resources, are limited, and data security advancements are lowly prioritised.

Furthermore, compounding on the lack of financial resources, a lack of BI Infrastructure was also identified as an inhibitor to BV realisation from BI [79]. According to [46], BI Infrastructure is expensive, mainly due to the various hardware and software required for adopters to handle and process the large volumes of data and add a substantial competitive advantage. In instances where some companies acquire BI tools, some would be so obsolete that they can negatively affect productivity due to slow speeds to run data [120].

A lack of skilled human resources is further explained by [46] where the paper illustrates the difficulties in acquiring skilled data scientists with domain knowledge as well as skilled personnel cable of handling large volumes of data. The data captured must be "cleaned" or synthesised into information, and very few professionals can execute this task proficiently, hence preventing BV realisation.

This point is further amplified by [120] describing some of the challenges BI personnel face, even from a data consumption perspective. According to some of the interviewees from the papers, data presentation is as equally important as the technical aspect that transpires in the background, as the legibility of the information acquired dictates integral aspects of the decision-making process which can significantly influence the trajectory of the organisation for the worse, if not executed properly.

According to [121], staff with limited skills and expertise to manage BI also find BI use difficult, resulting in the marginal application of the technology and thus resulting in low levels of BV realisation. The authors explain that the difficulty to utilise BI, if not controlled by staff training and exposure over time, can result in staff being demotivated, which furthers their negativity towards the use of the technology.

Ref. [121] also highlighted the lack of standard KPIs to evaluate firm performance (FP) and subsequently BV. For instance, the human resource KPI was conditioned solely to align managers with employee consultations, hence resulting in inaccuracies about an employee's performance and productivity.

Still, within the breast of data security, some organisations and departments within organisations are wary of sharing information with partners and other departments, as there is a fear of sensitive data leaking to competitors. For instance, partnering organisations with merged operational capabilities find themselves hesitant to expose all the operations and information to partnering firms due to the fear of exposure to unauthorised personnel who can take advantage of the organisation's weaknesses [46].

Firm size also contributes to the level of BV achieved from BI adoption, as larger organisations commonly have access to adequate resources for projects of this stature. These resources can catapult an organisation to further extremes of industrial competitiveness. Furthermore, larger firms are better equipped to accommodate BV latencies as compared to smaller firms, as results would be needed instantaneously since massive investments would have been injected into the business [122].

The authors in Ref [123] identified data-related problems that organisations face including data cleaning and preparation, data enrichment, and population imbalance. The authors also alluded to analytics challenges that organisations face, namely data volume dilemma changes such as comparisons of whether larger data volumes are better than algorithms, computational complexity, and analytic strategies. An overview of hindrances and inhibitors that were identified by different authors is shown in Table 8.

Table 8. Hindrances to the realisation of BV from BI.

Hindrance to BV Realisation	Sources of Mention
Data processing and handling issues	[76,91,92,99,124–126]
Data protection	[10,81,86,95,126,127]
Lack of BI Infrastructure	[10,79,86,99,125].
Lack of adequate skills and expertise	[60,79,86,125,128]
Lack of standard KPIs	[67,121,126]
Unliagnment of BI with organisational structure/culture	[64,91,126]
Lack of internal functional department cooperation	[46,99]
Firm size	[90,129]
Lack of resources due to unclear strategy	[64]
Lack of financial resources	[126]
Establishing governance	[91]

5.4. What Are the Different Forms of Business Value That Have Been Generated from BI Adoption in Organisations?

In [57], a definition from [130] was provided that explains value as "an enduring belief that a specific mode of conduct or end-state of existence is personally or socially preferable to an opposite or converse mode of conduct or end-state of existence". The definition indicates that value is a subjective term that can differ based on one's understanding and perspective on a phenomenon. This is the case with business value. This section will cover the different conceptions of BV.

According to [16], BV encompasses organisational benefits from analytics and the return on investment (ROI). Organisational benefits from analytics include the non-tangible benefits extracted from analytics (BI) such as "data-driven decision-making support to critical initiatives" (p. 653), organisational process upgrades, customer services querying, executive management decision-making improvements, business deliveries, innovations, management of risks, and improvement to knowledge management capital. On the other hand, ROI represents the measurable tangible aspects such as costs, benefits, profits, and revenues.

Other forms of the BV of BI can include the market share which is explained as the organisation's ability to increase influence within a specified market by establishing a concrete customer following and loyalty. This includes instances where the organisation is a new entry into a market or is introducing a new product so that the organisation can quickly capitalise and achieve industry dominance and recognition from the target group. BI can facilitate this process through advanced insights into the market, conducting internal and external analysis, which better inform management on how to devise the best strategic action plan to achieve market dominance [79,122].

KPIs come in different forms and are applied for various reasons which for one includes the assessment of FP. KPIs' measurement matrixes help organisations to evaluate the degree of success of an operation. Some examples of KPI employed include revenue increase, number of motor vehicle purchase cancellations, and customer vehicle review averages [131].

Ref. [122] illustrate a more detailed outline of examples of the BV of BI in organisations which they classified under four categories, namely partner relationship benefits, internal process efficiency benefits, customer intelligence benefits, and strategic organisational performance. The classifications are as follows:

A1: Customer intelligence benefits (e.g., improved products offering; improved customer service delivery, personalised product recommendation, customer service improvements)

A2: Business Process Performance (cost reduction and productivity enhancement)

A3: Improved organisational performance (e.g., Return on Investment (ROI); sales growth; monetary and non-monetary output, increased revenue; organisational efficiency)
A4: In-depth insight into the environment around the business
A5: Prediction of trends
A6: Better customer management and customer satisfaction
A7: Improved transparency
A8: Unique competitive advantage; improved market share
A9: Improved entrepreneurial insight into markets
A10: Improved learning processes
A11: Efficient process execution
A12: Better risk management
A13: Faster and more accurate recording
A14: Improved decision-making process
A15: IT savings and saving in other areas
A16: Improved and accurate Human Resource recruitment
Table 9 indicates the mapping of the classifications of BV by different authors

Table 9. BV classifications.

		Forms of Business Value														
S/*n*	Authors	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16
1	[8]	✓		✓													
2	[132]	✓	✓	✓	✓	✓											
3	[7]	✓						✓	✓								
4	[119]	✓								✓	✓						
5	[26]								✓			✓					
6	[96]	✓		✓					✓				✓	✓	✓	✓	
7	[122]		✓	✓													
8	[133]																✓
9	[64]																✓
10	[9]																✓
11	[134]																✓
12	[135]	✓	✓														
13	[131]	✓	✓														
14	[116]			✓													
15	[16]			✓													
16	[79]						✓										
17	[129]	✓							✓							✓	
18	[69]		✓									✓				✓	
19	[136]		✓	✓													
20	[88]			✓													
21	[92]			✓			✓										
22	[77]		✓	✓						✓							
23	[79]			✓													
24	[105]			✓		✓					✓	✓				✓	
25	[99]		✓						✓				✓		✓		
26	[72]			✓			✓			✓							

Table 9. *Cont.*

S/n	Authors	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16
										Forms of Business Value							
27	[137]			✓			✓										
28	[138]					✓		✓			✓	✓	✓				
29	[91]															✓	
30	[101]		✓			✓	✓		✓	✓							
31	[88]			✓			✓			✓							
32	[98]						✓					✓					
33	[84]								✓								
34	[52]			✓													
	Totals	8	9	16	1	4	7	2	7	5	4	5	2	2	2	4	4

6. Discussion

Based on the findings of this study, we observed the following:

6.1. Theories Used in BV Research So Far

The most employed theories in BV research are the Resource-Based View (RBV), Dynamic Capability theory (DCT), Technology Organisation Environment (TOE), and Contingency Theory (CON) (see Table 4), despite the wide variation in theories adopted over the years. RBV and DCT share the main characteristic: resources, which both theories heavily depend on to assess BV. The predominance of the use of RBV and DCT for studying BV and BI at the expense of other relevant theories suggests that more research that involves the use of new theoretical frameworks for studying the relationship between BV and BI adoption is required.

The TOE and CON are the third-most adopted theories in BV studies after RBV and DC. However, Sense Seize and Transform (SST), Business Process Theory (BPT), Value Theory (VT), Social Capital Theory (SCT), Knowledge-Based Dynamic Capability (KBDC), and Configurations Theory (COT) are the least employed.

The theories in Table 5 have been used scarcely thus far. Consequently, more studies that explore these scarcely used theories as a theoretical lens to study the relationship between BI and BV are desirable. This will further the understanding of issues of BV derivation from BI and the growth of perspectives on the relationship between BV and BI.

6.2. Critical Factors of BV

The most mentioned critical factors of BV derivation from BI are skilled human capital, BI Infrastructure, and data quality (See Table 6; Figure 3), with skilled human capital being the predominant factor mentioned in the literature. This emphasizes the importance of having skilled personnel within an organisation to achieve BV. The other critical factors that have received significant attention in the literature are BI applications and usage/data ceulture, BI alignment with organisational goals, and top management support. More studies on the impact of some critical factors such as clear organisational goals, governance regulations, BI adoption processes, organisational readiness, competitive pressure, organisational readiness, BI Investment, and latency effect are required to determine their impact on the derivation of BV from BI.

Concerning the application of theories for understanding the critical factors of BV derivation from BI, data quality has been investigated with more variations of theories than other BI critical factors (See Table 7). Dynamic capabilities, BI Infrastructure, top management involvement, and organisational agility/dynamism are the other critical factors that were studied with the application of various theoretical frameworks. The other critical factors of BV from BI that were studied with a moderate application of

theories are BI Infrastructure, BI application and usage/data culture, environmental factors, skilled human capital, governance regulations, organisational readiness, and BI-influenced decision-making. However, the critical factors for which few theories have been applied so far are clear organisational goals, procedural practices, BI adoption processes, competitive pressure, perceived benefits, organisational readiness, BI investment, planning, organising, and the latency effect. This suggests that more studies that are theoretically informed are needed to enable a better understanding of their impact as critical factors of BV derivation from BI.

From a DCT, CT, and VT perspective, the most commonly identified critical factors are dynamic capability and organisational agility, while BI Infrastructure and BI alignment with organisational goals are critical factors that are mentioned in studies that used DCT, RBV, DOI, and TOE to examine issues of BV in BI adoption (Table 7). Top management support and data quality are identified as critical by studies that used DCT, TOE, and DELTTA. Dynamic capability and data quality were acknowledged as critical in more papers than any other multiple factors and are considered as important in theories such as VT, DIKW, DCT, VT, and DIKW. There is a strong alignment of perspectives between TOE and DOI because both theories consider BI Infrastructure, BI alignment with organisational goals, top management support, governance regulations, competitive pressure, perceived benefits, and organisational readiness as critical factors of BI adoption.

In terms of coverage, DCT has the highest number of critical factors (11) for the derivation of business value from BI, while TOE and DOI focussed on the same set of 10 critical factors. The strong correlation between DOI and TOE in terms of critical factors stems from the fact that both theories are focussed on the adoption of technology in organisations, and actually, the TOE is a derivative of the DOI [115].

The Sociomaterialism Theory (SMT) has been mainly applied for studies that highlighted BI alignment, planning, and organising as critical elements to achieving BV. Social Capital Theory (SCT) was applied where governance regulations and BI decision making is considered imperative to realising BV. Knowledge-Based Dynamic Capability (KBDC) and Configurations Theory (COT) are mentioned in separate studies in which how BI influenced decision making and dynamic capabilities were regarded as critical factors.

So far, only the RBV theory considered the latency effect as a critical factor in the derivation of BV from BI. It will be essential to look more into the actual impact of the latency effect on the derivation of business value from BI.

6.3. Hindrances to BV

Data quality and handling were frequently mentioned as a major drawback to realising BV by several authors. They highlighted the need for quality data to produce the best strategies formulated from accurate insights [90,91,110]. Additionally, data security and protection were indicated as a worry for most practitioners despite emerging solutions such as cloud systems [124]. Another hindrance is the lack of BI Infrastructure. The lack of skilled human resource capital is also mentioned by many authors. This manifests in the form of a lack of adequate skills and expertise, lack of cooperation between internal functional departments within an organisation, and lack of standard KPIs (see Table 8). However, the issue of firm size, lack of resources due to an unclear strategy, lack of financial resources, and lack of governance were also identified as hindrances by very few authors. This suggests that more investigations on the less explored hindrances are essential to foster a deeper and more extensive understanding of the hindrances to BV.

6.4. Forms of BV

So far in the literature (see Table 9), the business value from BI adoption has been more consistently qualified in terms of customer intelligence (A1)—8 times (9.5%); business process performance (A2)—9 times (11.0%); improved organisational performance (A3)—16 times (19.5%); unique competitive advantage leading to an improved market share (A8)—7 times (8.5%); improved entrepreneurial insight into markets (A9)—5 times (6.1%);

and efficient process execution (A11)—5 times (6.1%). Apart from these six forms of BV, the others that were mentioned as forms of BV to a lesser extent are the prediction of trends (A5)—4 times (4.9%); improved learning processes (A10)—4 times (4.9%); IT savings and saving in other areas (A15)—4 times (4.9%); and improved and accurate human resource recruitment (A16)—4 times (4.9%). Other forms of BV such as in-depth insight into the environment around the business (A4); improved transparency (A7); better risk management (A12); faster and more accurate recording (A13); and improved decision-making processes (A14) are marginally mentioned in the literature which means that more studies are needed to validate their status as forms of BV that can be derived from BI.

7. Future Research Agenda

From the findings of this study, the following emergent research agenda is evident:

7.1. Need for More Theoretical Frameworks in the Study of BV Derivation from BI

Theories that have been used variously in research to clarify epistemological positions inform the logic for the selection of methods, analysis of data, and as a framework for a study [139]. So far, many theories were used as theoretical references in the study of the relationship between BV and BI. While theories such as RBV, DCT, and TOE were used prominently, several other theories were scarcely explored. Currently, in the literature, there is limited application of theories such as the Sense Seize and Transform perspective of the Dynamic capability Theory (DCT), Business Process Theory (BPT), Knowledge-Based View Theory (KBV), Systems Theory (ST), Value Theory (VT), Complexity Theory (CT), Diffusion of Innovation Theory (DOI), Social Capital Theory (SCT), Knowledge-Based Dynamic Capability (KBDC), and Configurations Theory (COT) to study the relationship between BI and BV. This suggests that there are opportunities to explore new knowledge on issues of BV derivation from BI, and such opportunities still exist particularly when these under-utilised theories are used as theoretical lenses to study the relationship between BV and BI.

The opportunity to explore the theories and frameworks that have yet to be sufficiently tested in BI and BV investigations could enable researchers to:

Conduct different types of empirical research on the relationship of BV and BI by using different methodologies (quantitative, qualitative, mixed-methods) as dictated by the strength and characteristics of the theories/frameworks that have been selected to underpin such studies;

Formulate new research aims and research questions in BI and BV research as influenced by the untested theories/frameworks;

Develop conceptual frameworks that explore a combination of relevant concepts that are selected from various untested theories to study complex issues in BV and BI research. For example, combining the Knowledge-Based Dynamic Capability (KBDC), Value Theory (VT), and Social Capital Theory to study the relationship between BI and BV in an organisation will provide rich insights on how issues of management of resources, social relationships, and knowledge management influence the competitive advantage that the organisation can derive as a form of business value from BI adoption. Thus, several opportunities exist to develop new conceptual frameworks that can be used to study how the interplay of different factors and the complex factorial relationships within an organisation affect BV derivation from BI. Studies that leverage innovative conceptual frameworks that are composed of untested theories are not yet commonplace in BI and BV research.

Explore new theoretical lenses for data collection, data analysis, and the interpretation of results, as informed by these untested theories/frameworks in BI and BV research.

All of these will help to clarify epistemological dispositions, broaden methodological choices, and aid further development of the theoretical body of knowledge on the relationship between BI and BV [140,141].

7.2. Need for More Perspectives on the Hindrances to BV Derivation

More investigations on the hindrances to BV derivation from BI are required, particularly those that consider the impact of firm size, lack of internal functional department cooperation, and challenges associated with data processing. Case studies that look at the correlation between these factors and BV derivation from BI are essential to enrich the current knowledge base on the issues of BV and BI.

The limited material on hindrances should explore other factors such as the alignment of BI with organisational structure/culture and the lack of necessary resources. Both are instrumental to BV realisation and a better understanding of these in different industrial settings can substantially improve the ROI from BI investments. Formulating a model compactable with specific industries can improve BV realisation and that is only possible if more in-depth research is conducted on aligning, completely, BI requirements with organisations' ethos.

7.3. Critical Factors of BV Derivation

So far, while many critical factors of BV derivation from BI have been identified, some of them such as clear organisational goals, procedural practices, BI adoption process, competitive pressure, perceived benefits, organisational readiness, BI investment, planning, organising, and the latency effect require more investigation to determine their effect on the derivation of BV from BI. This presents opportunities for researchers. More case studies with a focus on critical factors as their main research themes will be useful to deepen the understanding of the impact of these less explored critical factors on BV derivation from BI. Case studies on BV derivation from BI that focus on organisations that are located in the context of developing countries would be particularly valuable as very few of such currently exist in the extant literature [23,37].

7.4. Deeper Understanding of the Different Forms of BV

So far, relatively few forms of BV have been widely explored. There is a need for more studies that will focus on the less mentioned forms of business value from BI investments. The aspects that create opportunities for further studies include the prediction of trends (A5), improved learning processes (A10), IT savings and saving in other areas (A15), improved and accurate human resource recruitment (A16), in-depth insight into the environment around the business (A4), improved transparency (A7), improved entrepreneurial insight into markets (A9), efficient process execution (A11), better risk management (A12), and faster and more accurate recording (A13). New studies that focus on these themes will serve to validate or dispel claims about them as forms of BV, which will enrich the body of knowledge on BI research and benefit BI adopters and organisations.

8. Limitations and Future Research

The papers used for the study were those contained in the selected databases which are Google Scholar, Scopus, and Science Direct. We could have overlooked some relevant papers in the less prominent databases. The inclusion and exclusion criteria were instrumental in the selection processes, aiding with identifying the most relevant papers to this study and ensuring that all due diligence was applied within the consideration of the qualification of the papers. This was all possible through the selected search strings. However, there is a possibility that with other search strings other relevant papers could have been discovered and included in the paper. The examination of non-English papers can expand the reach of papers relevant to this study. The findings were a result of the analysis and processing of the selected papers to answer the four research questions of interest. Therefore, human error is possible and must be accounted for. Furthermore, the exclusion criteria included disregarding papers older than fifteen (15) years to ensure a timely relevance of selected papers to the topic of investigation; however, this could have resulted in some papers being excluded from the consideration of the study.

9. Conclusions

In this paper, we attempted to foster a deeper understanding of the relationship between BV and BI by focusing on four research questions that explore the theories that have been applied, critical factors for the derivation of BV from BI, inhibitors of BV, and the various forms of BV from BI to improve organisational ventures of longevity and sustainability.

Our findings show that the Resource-Based View (RBV), Dynamic Capability Theory (DCT), Technology Organisation Environment (TOE), and Contingency Theory (CON) are the theories most used to investigate the issue of BV from BI, while customer intelligence is the most acknowledged form of BV from BI. The main inhibitors of BV from BI are challenges related to data quality and handling, data security and protection, a lack of BI Infrastructure, and a lack of skilled human resource capital. We also found that skilled human capital, BI Infrastructure, data quality, BI application and usage/data culture, BI alignment with organisational goals, and top management support are the most acknowledged critical factors in BV from BI adoption. Some critical factors such as clear organisational goals, skilled human capital, governance regulations, BI adoption processes, organisational readiness, competitive pressure, organisational readiness, BI investment, and the latency effect require more investigation to determine their effect on the derivation of BV from BI.

To the best of our knowledge, no previous study has offered the same detailed and targeted perspective on the relationship between BV derivation and BI adoption. Thus, as a contribution, the study offers a useful intellectual guide for BI researchers, BI practitioners, and organisations on pertinent issues that can aid the derivation of BV from BI.

In future work, we shall conduct some empirical studies as a follow-up to the findings of this study, particularly in the areas of understanding the impact of specific critical factors on the derivation of BV from BI adoption in organisations with a specific interest in those factors that have not been widely mentioned in the literature. Moreover, we shall conduct studies that use new theoretical lenses to study relationships between BI and BV, with an emphasis on theories that have been marginally explored on the topic. Another possibility to be explored is to conduct empirical studies that will employ an integration of concepts from various theories to investigate issues of BV derivation from BI. This would be conducted in the hope that it promotes a deeper understanding of the issues of BV from BI adoption and extends the body of knowledge in BI adoption research.

References

1. Trieu, V.-H. Getting value from Business Intelligence systems: A review and research agenda. *Decis. Support Syst.* **2017**, *93*, 111–124. [CrossRef]
2. Bach, M.P.; Jaklič, J.; Vugec, D.S. Understanding impact of business intelligence to organizational performance using cluster analysis: Does culture matter? *Int. J. Inf. Syst. Proj. Manag.* **2018**, *6*, 63–86. [CrossRef]
3. El-Haddadeh, R.; Osmani, M.; Hindi, N.; Fadlalla, A. Value creation for realising the sustainable development goals: Fostering organisational adoption of big data analytics. *J. Bus. Res.* **2021**, *131*, 402–410. [CrossRef]

4. Aydiner, A.S.; Tatoglu, E.; Bayraktar, E.; Zaim, S.; Delen, D. Business analytics and firm performance: The mediating role of business process performance. *J. Bus. Res.* **2019**, *96*, 228–237. [CrossRef]

5. Božič, K.; Dimovski, V. Business intelligence and analytics use, innovation ambidexterity, and firm performance: A dynamic capabilities perspective. *J. Strat. Inf. Syst.* **2019**, *28*, 101578. [CrossRef]

6. Shanks, G.; Sharma, R. Creating value from business analytics systems: The impact of strategy. In Proceedings of the 15th Pacific Asia Conference on Information Systems: Quality Research in Pacific, PACIS 2011, Queensland University of Technology, Queensland, Australia, 7–11 July 2011; pp. 1–12.

7. Yadegaridehkordi, E.; Nilashi, M.; Shuib, L.; Nasir, M.H.N.B.M.; Asadi, S.; Samad, S.; Awang, N.F. The impact of big data on firm performance in hotel industry. *Electron. Commer. Res. Appl.* **2020**, *40*, 100921. [CrossRef]

8. Dong, J.Q.; Yang, C.-H. Business value of big data analytics: A systems-theoretic approach and empirical test. *Inf. Manag.* **2020**, *57*, 103124. [CrossRef]

9. Côrte-Real, N.; Ruivo, P.; Oliveira, T.; Popovič, A. Unlocking the drivers of big data analytics value in firms. *J. Bus. Res.* **2019**, *97*, 160–173. [CrossRef]

10. Wang, S.; Yeoh, W.; Richards, G.; Wong, S.F.; Chang, Y. Harnessing business analytics value through organizational absorptive capacity. *Inf. Manag.* **2019**, *56*, 103152. [CrossRef]

11. Božič, K.; Dimovski, V. Business intelligence and analytics for value creation: The role of absorptive capacity. *Int. J. Inf. Manag.* **2019**, *46*, 93–103. [CrossRef]

12. Torres, R.; Sidorova, A.; Jones, M.C. Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective. *Inf. Manag.* **2018**, *55*, 822–839. [CrossRef]

13. Sardi, A.; Sorano, E.; Cantino, V.; Garengo, P. Big data and performance measurement research: Trends, evolution and future opportunities. *Meas. Bus. Excel.* **2019**, *2020*. [CrossRef]

14. Popovič, A.; Hackney, R.; Coelho, P.S.; Jaklič, J. Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decis. Support Syst.* **2012**, *54*, 729–739. [CrossRef]

15. Ren, S.J.-F.; Wamba, S.F.; Akter, S.; Dubey, R.; Childe, S.J. Modelling quality dynamics, business value and firm performance in a big data analytics environment. *Int. J. Prod. Res.* **2017**, *55*, 5011–5026. [CrossRef]

16. Krishnamoorthi, S.; Mathew, S.K. Business analytics and business value: A comparative case study. *Inf. Manag.* **2018**, *55*, 643–666. [CrossRef]

17. Jacobs, L.G.; Leipzig, R.M. Why Systematic Reviews? *J. Am. Geriatr. Soc.* **2000**, *48*, 1743–1744. [CrossRef]

18. Chen, Y.; Lin, Z. Business Intelligence Capabilities and Firm Performance: A Study in China. *Int. J. Inf. Manag.* **2021**, *57*, 102232. [CrossRef]

19. Nam, D.; Lee, J.; Lee, H. Business analytics use in CRM: A nomological net from IT competence to CRM performance. *Int. J. Inf. Manag.* **2019**, *45*, 233–245. [CrossRef]

20. Shanks, G.; Sharma, R.; Seddon, P.; Reynolds, P. The impact of strategy and maturity on business analytics and firm performance: A review and research agenda. In Proceedings of the ACIS 2010 Proceedings 21st Australasian Conference on Information Systems, Brisbane, Australia, 1–3 December 2010.

21. Shanks, G.; Bekmamedova, N. Creating value with business analytics in the supply chain. In *ECIS 2013 Completed Research*; Association for Information Systems (AIS): Utrecht, The Netherland, 2013; pp. 1–12.

22. Mishra, D.; Luo, Z.; Hazen, B.; Hassini, E.; Foropon, C. Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance. *Manag. Decis.* **2019**, *57*, 1734–1755. [CrossRef]

23. Fatima, A.; Linnes, C. The Current Status of Business Intelligence: A Systematic Literature Review. *Am. J. Inf. Technol.* **2019**, *9*, 1–21.

24. Abai, N.H.Z.; Yahaya, J.; Deraman, A.; Hamdan, A.R.; Mansor, Z.; Jusoh, Y.Y. Integrating Business Intelligence and Analytics in Managing Public Sector Performance: An Empirical Study. *Int. J. Adv. Sci. Eng. Inf. Technol.* **2019**, *9*, 172–180. [CrossRef]

25. Yeoh, W.; Gao, J.; Koronios, A. Towards a Critical Success Factor Framework for Implementing Business Intelligence Systems: A Delphi Study in Engineering Asset Management Organizations. *IFIP Int. Fed. Inf. Process.* **2007**, *255*, 1353–1367. [CrossRef]

26. Seddon, P.B.; Constantinidis, D.; Tamm, T.; Dod, H. How does business analytics contribute to business value? *Inf. Syst. J.* **2016**, *27*, 237–269. [CrossRef]

27. Davenport, T.H. Competing on analytics. *Harv. Bus. Rev.* **2006**, *84*, 1–9.

28. Chen, H.; Storey, V.C. Business Intelligence and Impact: From Big Data to Big Impact. *MIS Q.* **2012**, *36*, 1165–1188. [CrossRef]

29. Kiron, D.; Shockley, R. Creating Business Value with Analytics. *MIT Sloan Manag. Rev.* **2011**, *53*, 57–63.

30. Ghasemaghaei, M.; Calic, G. Assessing the impact of big data on firm innovation performance: Big data is not always better data. *J. Bus. Res.* **2020**, *108*, 147–162. [CrossRef]

31. Kollwitz, C.; Dinter, B.; Krawatzeck, R.; Pieczkiewicz, D.S. *Analytics and Data Science: Advances in Research and Pedagogy*, 1st ed.; Springer: Hamburg, Germany, 2018.

32. Bronzo, M.; De Resende, P.T.V.; De Oliveira, M.P.V.; McCormack, K.P.; De Sousa, P.R.; Ferreira, R.L. Improving performance aligning business analytics with process orientation. *Int. J. Inf. Manag.* **2013**, *33*, 300–307. [CrossRef]

33. Gupta, M.; George, J. Toward the development of a big data analytics capability. *Inf. Manag.* **2016**, *53*, 1049–1064. [CrossRef]

34. Ashrafi, A.; ZareRavasan, A.; Trkman, P.; Afshari, S. The role of business analytics capabilities in bolstering firms' agility and performance. *Int. J. Inf. Manag.* **2019**, *47*, 1–15. [CrossRef]

35. Işık, Ö.; Jones, M.C.; Sidorova, A. Business intelligence success: The roles of BI capabilities and decision environments. *Inf. Manag.* **2013**, *50*, 13–23. [CrossRef]

36. Bedeley, R.T.; Ghoshal, T.; Iyer, L.S.; Bhadury, J. Business Analytics and Organisational Value chains: A Relational Mapping. *J. Comput. Inf. Syst.* **2018**, *58*, 151–161.

37. Ain, N.; Vaia, G.; DeLone, W.H.; Waheed, M. Two decades of research on business intelligence system adoption, utilization and success—A systematic literature review. *Decis. Support Syst.* **2019**, *125*, 113113. [CrossRef]

38. English, V.; Hoffmann, M. Business Intelligence as a Source of Competitive Advantage in SMEs: A Systematic Review. *DBS Bus. Rev.* **2018**, *2*, 10–32. [CrossRef]

39. Jaklič, J.; Grublješič, T.; Popovič, A. The role of compatibility in predicting business intelligence and analytics use intentions. *Int. J. Inf. Manag.* **2018**, *43*, 305–318. [CrossRef]

40. Lautenbach, T.A.-O.; Johnston, P.K. Factors influencing business intelligence and analytics usage extent in South African organisations. *S. Afr. J. Bus. Manag.* **2017**, *48*, 23–33.

41. Côrte-Real, N.; Ruivo, P.; Oliveira, T. The Diffusion Stages of Business Intelligence & Analytics (BI&A): A Systematic Mapping Study. *Procedia Technol.* **2014**, *16*, 172–179. [CrossRef]

42. Keele, S. *Guidelines for Performing Systematic Literature Reviews in Software Engineering*; Technical Report, Ver. 2.3 EBSE Technical Report; University of Durham: Durham, UK, 2007.

43. Höst, M.; Oručević-Alagić, A. A systematic review of research on open source software in commercial software product development. *Inf. Softw. Technol.* **2011**, *53*, 616–624. [CrossRef]

44. Côrte-Real, N.T.O.; Ruivo, P.; Oliveira, T.; Ruivo, P. Understanding the hidden value of business intelligence and analytics (BI&A). *Twent. Am. Conf. Inf. Syst.* **2014**, *2012*, 1–10.

45. Müller, S.D.; Jensen, P. Big data in the Danish industry: Application and value creation. *Bus. Process. Manag. J.* **2017**, *23*, 645–670. [CrossRef]

46. Verma, S.; Bhattacharyya, S.S. Perceived strategic value-based adoption of Big Data Analytics in emerging economy. *J. Enterp. Inf. Manag.* **2017**, *30*, 354–382. [CrossRef]

47. Teece, D.J.; Pisano, G.; Shuen, A. Dynamic Capabilities and Strategic Management. *Essays Technol. Manag. Policy* **2003**, *18*, 77–120. [CrossRef]

48. Delone, W.H.; McLean, E.R. The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *J. Manag. Inf. Syst.* **2003**, *19*, 9–30. [CrossRef]

49. Arnold, U. Organization of global sourcing: Ways towards an optimal degree of centralization. *Eur. J. Purch. Supply Manag.* **1999**, *5*, 167–174. [CrossRef]

50. Pennings, J.M.; Johannes, M. The Relevance of the Structural-Contingency Model for Organizational Effectiveness. *Adm. Sci. Q.* **1975**, *20*, 393–410. [CrossRef]

51. Venkatraman, N. The Concept of Fit in Strategy Research: Toward Verbal and Statistical Correspondence. *Acad. Manag. Rev.* **1989**, *14*, 423–444. [CrossRef]

52. Jayakrishnan, M.; Mohamad, A.K.; Azmi, F.R.; Abdullah, A. Implementation of business intelligence framework for Malaysian halal food manufacturing industry towards initiate strategic financial performance management. *Manag. Sci. Lett.* **2018**, *8*, 1059–1076. [CrossRef]

53. Grant, R. Prospering in Dynamically-Competitive Environments: Organizational Capability as Knowledge Integration. *Knowl. Strategy* **1999**, *7*, 133–153. [CrossRef]

54. Ylijoki, O.; Porras, J. A recipe for big data value creation. *Bus. Process. Manag. J.* **2019**, *25*, 1085–1100. [CrossRef]

55. Kaplan, R.S.; Norton, D.P. Putting the Balanced Scorecard to Work. *Econ. Impact Knowl.* **1993**, *315*. [CrossRef]

56. Ackoff, R.L. Towards a system of systems concepts. *Manag. Sci.* **1971**, *17*, 661–671. [CrossRef]

57. Dooley, P.P.; Levy, Y.; Hackney, R.A.; Parrish, J.L. Critical Value Factors in Business Intelligence Systems Implementations. *Anal. Data Sci.* **2018**, 55–78.

58. Wu, P.-L.; Yeh, S.-S.; Huan, T.-C.; Woodside, A.G. Applying complexity theory to deepen service dominant logic: Configural analysis of customer experience-and-outcome assessments of professional services for personal transformations. *J. Bus. Res.* **2014**, *67*, 1647–1670. [CrossRef]

59. Tornatzky, L.; Fleischer, M. *The Processes of Technological Innovation*; Lexington Books: Lexington, MA, USA, 1990.

60. Popovič, A.; Puklavec, B.; Oliveira, T. Justifying business intelligence systems adoption in SMEs. *Ind. Manag. Data Syst.* **2019**, *119*, 210–228. [CrossRef]

61. Rodgers, E.; Singhal, A.; Quinlan, M. *Diffusion of Innovations*; Routledge: New York, NY, USA, 1995.

62. Soh, C.; Markus, M.L. How IT Creates Business Value: A Process Theory Synthesis. 1995. Available online: http://aisel.aisnet.org/icis1995/4 (accessed on 23 March 2021).

63. Smart, J. Linked references are available on JSTOR for this article. *Acad. Manag. Rev.* **1963**, *60*, 651–662.

64. Shamim, S.; Zeng, J.; Khan, Z.; Zia, N.U. Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technol. Forecast. Soc. Chang.* **2020**, *161*, 120315. [CrossRef]

65. Mikalef, P.; Pateli, A.; Batenburg, R.; Van De Wetering, R. Purchasing alignment under multiple contingencies: A configuration theory approach. *Ind. Manag. Data Syst.* **2015**, *115*, 625–645. [CrossRef]

66.　Wamba, S.F.; Akter, S.; Trinchera, L.; De Bourmont, M. Turning information quality into firm performance in the big data economy. *Manag. Decis.* **2019**, *57*, 1756–1783. [CrossRef]

67.　Jeble, S.; Kumari, S.; Venkatesh, V.; Singh, M. Influence of big data and predictive analytics and social capital on performance of humanitarian supply chain. *Benchmarking Int. J.* **2019**, *27*, 606–633. [CrossRef]

68.　Vitari, C.; Raguseo, E. Big data analytics business value and firm performance: Linking with environmental context. *Int. J. Prod. Res.* **2020**, *58*, 5456–5476. [CrossRef]

69.　Yogev, N.; Even, A.; Fink, L. How Business Intelligence Creates Value. *Int. J. Bus. Intell. Res.* **2013**, *4*, 16–31. [CrossRef]

70.　Chae, B.; Yang, C.; Olson, D.; Sheu, C. The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective. *Decis. Support Syst.* **2014**, *59*, 119–126. [CrossRef]

71.　Fink, L.; Yogev, N.; Even, A. Business intelligence and organizational learning: An empirical investigation of value creation processes. *Inf. Manag.* **2017**, *54*, 38–56. [CrossRef]

72.　Wamba, S.F.; Gunasekaran, A.; Akter, S.; Ren, S.J.-F.; Dubey, R.; Childe, S.J. Big data analytics and firm performance: Effects of dynamic capabilities. *J. Bus. Res.* **2017**, *70*, 356–365. [CrossRef]

73.　Ferraris, A.; Mazzoleni, A.; DeValle, A.; Couturier, J. Big data analytics capabilities and knowledge management: Impact on firm performance. *Manag. Decis.* **2019**, *57*, 1923–1936. [CrossRef]

74.　Upadhyay, P.; Kumar, A. The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. *Int. J. Inf. Manag.* **2020**, *52*, 102100. [CrossRef]

75.　Behl, A. Antecedents to firm performance and competitiveness using the lens of big data analytics: A cross-cultural study. *Manag. Decis.* **2020**, in press. [CrossRef]

76.　Aljumah, A.I.; Nuseir, M.T.; Alam, M. Organizational performance and capabilities to analyze big data: Do the ambidexterity and business value of big data analytics matter? *Bus. Process. Manag. J.* **2021**, *27*, 1088–1107. [CrossRef]

77.　Yasmin, M.; Tatoglu, E.; Kilic, H.S.; Zaim, S.; Delen, D. Big data analytics capabilities and firm performance: An integrated MCDM approach. *J. Bus. Res.* **2020**, *114*, 1–15. [CrossRef]

78.　Liu, C.-H.; Mehandjiev, N. The Effect of Big Data Analytics Capability on Firm Performance: A Pilot Study in China. *Bus. Inf. Syst.* **2020**, *381*, 594–608. [CrossRef]

79.　Maroufkhani, P.; Wagner, R.; Ismail, W.K.W.; Baroto, M.B.; Nourani, M. Big Data Analytics and Firm Performance: A Systematic Review. *Information* **2019**, *10*, 226. [CrossRef]

80.　Anfer, O.; Wamba, S.F. Big Data Analytics and Strategic Marketing Capabilities: Impact on Firm Performance. *Adv. Intell. Syst. Comput.* **2019**, *931*, 633–640. [CrossRef]

81.　Maroufkhani, P.; Tseng, M.-L.; Iranmanesh, M.; Ismail, W.K.W.; Khalid, H. Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *Int. J. Inf. Manag.* **2020**, *54*, 102190. [CrossRef]

82.　Seddon, P.B.; Constantinidis, D. Through what mechanisms does business analytics contribute to business value? In Proceedings of the Pacific Asia Conference on Information Systems, PACIS 2012, Chi Minh City, Vietnam, 11–15 July 2012; pp. 1–12.

83.　Hartmann, E.; Trautmann, G.; Jahns, C. Organisational design implications of global sourcing: A multiple case study analysis on the application of control mechanisms. *J. Purch. Supply Manag.* **2008**, *14*, 28–42. [CrossRef]

84.　Côrte-Real, N.; Ruivo, P.; Oliveira, T. Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value? *Inf. Manag.* **2020**, *57*, 103141. [CrossRef]

85.　Shenzhen, S.; Jifan, R. *Firm Performance? An Empirical Study Based on the Dynamic Capabilities Theory*; 2018; pp. 1–4.

86.　Lamba, H.S.; Dubey, S. Analysis of requirements for Big Data Adoption to maximize IT Business Value. In Proceedings of the 2015 4th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO), Noida, India, 2–4 September 2015; pp. 1–6.

87.　Gu, V.C.; Zhou, B.; Cao, Q.; Adams, J. Exploring the relationship between supplier development, big data analytics capability, and firm performance. *Ann. Oper. Res.* **2021**, *302*, 151–172. [CrossRef]

88.　Razaghi, S.; Shokouhyar, S. Impacts of big data analytics management capabilities and supply chain integration on global sourcing: A survey on firm performance. *Bottom Line* **2021**, in press. [CrossRef]

89.　Akter, S.; Wamba, S.F.; Gunasekaran, A.; Dubey, R.; Childe, S.J. How to improve firm performance using big data analytics capability and business strategy alignment? *Int. J. Prod. Econ.* **2016**, *182*, 113–131. [CrossRef]

90.　Mikalef, P.; Boura, M.; Lekakos, G.; Krogstie, J. Big data analytics and firm performance: Findings from a mixed-method approach. *J. Bus. Res.* **2019**, *98*, 261–276. [CrossRef]

91.　Mikalef, P.; Framnes, V.A.; Danielsen, F.; Krogstie, J.; Olsen, D.H. Big data analytics capability: Antecedents and business value. In Proceedings of the 21st Pacific Asia Conference on Information Systems, PACIS 2017, Langkawi, Malaysia, 16–20 July 2017.

92.　Arias-Pérez, J.; Coronado-Medina, A.; Perdomo-Charry, G. Big data analytics capability as a mediator in the impact of open innovation on firm performance. *J. Strat. Manag.* **2021**, in press. [CrossRef]

93.　Côrte-Real, N.; Oliveira, T.; Ruivo, P. Assessing business value of Big Data Analytics in European firms. *J. Bus. Res.* **2017**, *70*, 379–390. [CrossRef]

94.　Sumbal, M.S.; Tsui, E.; Irfan, I.; Shujahat, M.; Mosconi, E.; Ali, M. Value creation through big data application process management: The case of the oil and gas industry. *J. Knowl. Manag.* **2019**, *23*, 1566–1585. [CrossRef]

95.　Mawed, M.; Al-Hajj, A. Using big data to improve the performance management: A case study from the UAE FM industry. *Facilities* **2017**, *35*, 746–765. [CrossRef]

96. Owusu, A. Business intelligence systems and bank performance in Ghana: The balanced scorecard approach. *Cogent Bus. Manag.* **2017**, *4*, 1364056. [CrossRef]

97. Jayakrishnan, M.A.L.; Bin Mohamad, A.K.; Yusof, M.B.M. The holistic view of business intelligence (BI) and big data analytics (BDA) towards designing strategic performance management framework: A case study. *J. Theor. Appl. Inf. Technol.* **2018**, *96*, 2025–2045.

98. Someh, I.A.; Shanks, G. The role of synergy in achieving value from Business Analytics systems. *Reshaping Soc. Through Inf. Syst. Des.* **2013**, *5*, 4180–4195.

99. Fay, M.; Kazantsev, N. When smart gets smarter: How big data analytics creates business value in smart manufacturing. *Int. Conf. Inf. Syst.* **2018**, *2018*, 1–9.

100. Brinch, M. Understanding the value of big data in supply chain management and its business processes. *Int. J. Oper. Prod. Manag.* **2018**, *38*, 1589–1614. [CrossRef]

101. Mikalef, P.; Boura, M.; Lekakos, G.; Krogstie, J. Configurations of big data analytics for firm performance: An fsQCA approach. In Proceedings of the 25th Americas Conference on Information Systems, AMCIS 2019, Cancun, Mexico, 15–17 August 2019; pp. 1–10.

102. Lane, M.; Stagg, A. University staff adoption of iPads: An empirical study using an extended technology acceptance model. *Australas. J. Inf. Syst.* **2014**, *18*, 53–74.

103. Bordeleau, F.-E.; Mosconi, E.; De Santa-Eulalia, L.A. Business intelligence and analytics value creation in Industry 4.0: A multiple case study in manufacturing medium enterprises. *Prod. Plan. Control* **2019**, *31*, 173–185. [CrossRef]

104. Tamm, T.; Seddon, P.; Shanks, G. Pathways to value from business analytics. In Proceedings of the Thirty Fourth International Conference on Information Systems, Milan, Italy, 15–18 December 2013; Volume 4, pp. 2915–2930.

105. Popovič, A.; Hackney, R.; Tassabehji, R.; Castelli, M. The impact of big data analytics on firms' high value business performance. *Inf. Syst. Front.* **2018**, *20*, 209–222. [CrossRef]

106. Goebel, R.; Norman, A.; Karanasios, S. Exploring the value of business analytics solutions for SMEs. In Proceedings of the UK Academy for Information Systems Conference, Oxford, UK, 16–18 March 2015; Volume 22, pp. 2–31.

107. Peters, M.D.; Wieder, B.; Sutton, S.G.; Wakefield, J. Business intelligence systems use in performance measurement capabilities: Implications for enhanced competitive advantage. *Int. J. Account. Inf. Syst.* **2016**, *21*, 1–17. [CrossRef]

108. Mikalef, P.; Pappas, I.O.; Krogstie, J.; Pavlou, P.A. Big data and business analytics: A research agenda for realizing business value. *Inf. Manag.* **2020**, *57*, 103237. [CrossRef]

109. Liang, T.-P.; Liu, Y.-H. Research Landscape of Business Intelligence and Big Data analytics: A bibliometrics study. *Expert Syst. Appl.* **2018**, *111*, 2–10. [CrossRef]

110. Wamba, S.F.; Akter, S.; de Bourmont, M. Quality dominant logic in big data analytics and firm performance. *Bus. Process. Manag. J.* **2019**, *25*, 512–532. [CrossRef]

111. Jifa, G.; Lingling, Z. Data, DIKW, Big Data and Data Science. *Procedia Comput. Sci.* **2014**, *31*, 814–821. [CrossRef]

112. Abai, N.H.Z.; Yahaya, J.H.; Deraman, A. The determinants of integrated business intelligence and analytics in organisational performance process. In Proceedings of the 2017 6th International Conference on Electrical Engineering and Informatics (ICEEI), Langkawi, Malaysia, 25–27 November 2017; Volume 2017, pp. 1–6. [CrossRef]

113. Van De Wetering, R.; Mikalef, P.; Krogstie, J. Big Data is Power: Business Value from a Process Oriented Analytics Capability. *Bus. Inf. Syst.* **2019**, *339*, 468–480. [CrossRef]

114. Elbashir, M.Z.; Collier, P.A.; Sutton, S.; Davern, M.; Leech, S.A. Enhancing the Business Value of Business Intelligence: The Role of Shared Knowledge and Assimilation. *J. Inf. Syst.* **2013**, *27*, 87–105. [CrossRef]

115. Hackney, R.A.; Dooley, P.; Levvy, Y.; Parrish, J. Critical value factors in business intelligence systems implementation success: An empirical analysis of system and information quality. *Int. Conf. Inf. Syst.* **2015**, *48*, 11970.

116. Aris, K. Business Intelligence and Analytics: The Mechanism of Business Value Creation. Ph.D. Thesis, University of Patras, Patras, Greece, 2019.

117. Ghasemaghaei, M. Understanding the impact of big data on firm performance: The necessity of conceptually differentiating among big data characteristics. *Int. J. Inf. Manag.* **2021**, *57*, 102055. [CrossRef]

118. Caputo, F.; Cillo, V.; Candelo, E.; Liu, Y. Innovating through digital revolution. *Manag. Decis.* **2019**, *57*, 2032–2051. [CrossRef]

119. Gnizy, I. Big data and its strategic path to value in international firms. *Int. Mark. Rev.* **2019**, *36*, 318–341. [CrossRef]

120. Conboy, K.; Dennehy, D.; O'Connor, M. 'Big time': An examination of temporal complexity and business value in analytics. *Inf. Manag.* **2020**, *57*, 103077. [CrossRef]

121. Vallurupalli, V.; Bose, I. Business intelligence for performance measurement: A case based analysis. *Decis. Support Syst.* **2018**, *111*, 72–85. [CrossRef]

122. Elbashir, M.Z.; Collier, P.A.; Davern, M.J. Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. *Int. J. Account. Inf. Syst.* **2008**, *9*, 135–153. [CrossRef]

123. Ratia, M.; Myllärniemi, J.; Helander, N. The new era of business intelligence. *Meditari Account. Res.* **2018**, *26*, 531–546. [CrossRef]

124. Kaisler, S.H.; Espinosa, J.A.; Armour, F.; Money, W.H. Advanced analytics—Issues and challenges in a global environment. In Proceedings of the 2014 47th Hawaii International Conference on System Sciences, Waikoloa, HI, USA, 6 January 2014; pp. 729–738. [CrossRef]

125. Clavier, P.R.; Lotriet, H.H.; van Loggerenberg, J.J. Towards a BI Value Coin: Applying Service Research to Address Business Intelligence Challenges. In Proceedings of the 2014 47th Hawaii International Conference on System Sciences, Waikoloa, HI, USA, 6–9 January 2014; pp. 1324–1333. [CrossRef]

126. Arora, D.; Malik, P. Analytics: Key to go from generating big data to deriving business value. In Proceedings of the 2015 IEEE First International Conference on Big Data Computing Service and Applicationsl, Redwood City, CA, USA, 25 August 2015; pp. 446–452. [CrossRef]

127. Bhosale, M.; Ukhalkar, P. The Role of Big Data in Enhancing Business Value through Business Intelligence and Big Data Analytics. 2020. Available online: https://www.researchgate.net/publication/344432858 (accessed on 23 March 2021).

128. Kibe, L.W.; Kwanya, T.; Owano, A. Relationship between big data analytics and organisational performance of the Technical University of Kenya and Strathmore University in Kenya. *Glob. Knowl. Mem. Commun.* **2020**, *69*, 537–556. [CrossRef]

129. Llave, M.R.; Hustad, E.; Olsen, D.H. Creating value from business intelligence and analytics in SMEs: Insights from experts. In Proceedings of the Americas Conference on Information Systems 2018: Digital Disruption, AMCIS 2018, New Orleans, MS, USA, 16–18 August 2018; pp. 1–10.

130. Rokeach, M. *The Nature of Human Values*; Free Press: New York, NY, USA, 1973.

131. Maté, A.; Trujillo, J.; Mylopoulos, J. Specification and derivation of key performance indicators for business analytics: A semantic approach. *Data Knowl. Eng.* **2017**, *108*, 30–49. [CrossRef]

132. Elia, G.; Polimeno, G.; Solazzo, G.; Passiante, G. A multi-dimension framework for value creation through Big Data. *Ind. Mark. Manag.* **2020**, *90*, 617–632. [CrossRef]

133. Kim, J.; Dibrell, C.; Kraft, E.; Marshall, D. Data analytics and performance: The moderating role of intuition-based HR management in major league baseball. *J. Bus. Res.* **2021**, *122*, 204–216. [CrossRef]

134. Ben-Gal, H.C. An ROI-based review of HR analytics: Practical implementation tools. *Pers. Rev.* **2019**, *48*, 1429–1448. [CrossRef]

135. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Bryde, D.J.; Giannakis, M.; Foropon, C.; Roubaud, D.; Hazen, B.T. Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *Int. J. Prod. Econ.* **2020**, *226*, 107599. [CrossRef]

136. Popovič, A.; Turk, T.; Jaklič, J. Conceptual model of business value of business intelligence systems. *Manag. J. Contemp. Manag.* **2010**, *15*, 5–30.

137. Raguseo, E.; Vitari, C. Investments in big data analytics and firm performance: An empirical investigation of direct and mediating effects. *Int. J. Prod. Res.* **2018**, *56*, 5206–5221. [CrossRef]

138. Grover, V.; Chiang, R.H.; Liang, T.-P.; Zhang, D. Creating Strategic Business Value from Big Data Analytics: A Research Framework. *J. Manag. Inf. Syst.* **2018**, *35*, 388–423. [CrossRef]

139. Ngulube, P.; Mathipa, E.; Gumbo, M. Theoretical and conceptual frameworks in the social and management sciences. In *Addressing Research Challenges: Making Headway in Developing Researchers*; Mosala-MASEDI Publishers & Booksellers cc: Noordyw, South Africa, 2015; pp. 43–66.

140. Stewart, D.; Klein, S. The use of theory in research. *Int. J. Clin. Pharm.* **2016**, *38*, 615–619. [CrossRef] [PubMed]

141. Collins, C.S.; Stockton, C.M. The Central Role of Theory in Qualitative Research. *Int. J. Qual. Methods* **2018**, *17*, 1609406918797475. [CrossRef]