

## Article

# Understanding the Relationship between Big Data Analytics Capabilities and Sustainable Performance: The Role of Strategic Agility and Firm Creativity

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**Abstract:** The most successful organisations create businesses that can respond to sudden and unexpected changes in the market. The purpose of this research is to examine how big data analytics capabilities might, through strategic agility, impact on sustainable performance. We grounded our theoretical framework in two perspectives: the resource-based view and the dynamic capabilities view. In order to gather data from Saudi Arabian managers, we used the positivist methodology of a survey. Data were collected from 410 managers. The data were analysed using the SEM method. The findings indicated that big data analytics capabilities have a significant effect on economic, environmental, and social performance. They also revealed that strategic agility partially mediates the relationship between the capabilities of big data analytics and sustainable performance. Furthermore, the impact of big data analytics capabilities on strategic agility is stronger in a creative environment, while the strategic agility–sustainable performance relationship is more pronounced in more creative environments. The findings offer firms an insight into the actual benefits that big data analytics may generate and how firms may align the use of big data analytics with industrial conditions to foster sustainable performance.

**Keywords:** big data analytics capabilities; strategic agility; sustainable performance; firm creativity



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## 1. Introduction

In today's market, businesses wanting to be competitive are embracing new and developing technology to speed up production, improve quality control, and offer more individualised services [1–3]. The advent of big data in recent years has presented businesses with numerous new opportunities to offset the challenges that come with them. Businesses which have embraced big data analytics (BDA) have seen a number of advantages [4]. In addition, data-driven decision making has become increasingly significant over the past couple of decades [1,5], thanks to the proliferation of the internet, social media, and mobile devices which allow vast amounts of information to be collected and analysed [6,7]. Internet data are expected to reach 163 trillion gigabytes by 2025, according to an estimate published by IDC in April 2017 [8,9]. Increases in data processing power [10] have also facilitated the development of a number of interconnected and often duplicated business intelligence tools [11]. The term big data is often used to describe programmes of this kind [12,13]. BDA is commonly regarded as a helpful enabler for identifying high- and low-performing organisations [14]. Examples of Target Corporation's use of BDA for sales forecasting can be found in the literature. By using consumer suggestions as a means of persuasion, Amazon.com is also making use of BDA [15]. GE also plans to use BDA to improve coordination between its gas and power systems, resulting in USD 66 billion in fuel savings

over the next 15 years [16,17]. As a result, businesses are focusing on BDA as a means of improving the efficiency of both their everyday and their long-term operations [18–20].

Big data analytics capabilities (BDACs), according to the literature, help businesses adapt to the ever-changing demands of the market and the factory floor [21]. Dynamic capacities (DCs) have been shown empirically to have a moderating effect on the connection between BDACs and firm performance [22,23]. Although most prior research established a favourable link between BDACs and company performance, recent research [7,24] has seen the relationship between BDACs and firm agility as inconclusive [25,26]. However, most of the literature agrees that BDACs are a valuable asset for enhancing performance, especially in industrial settings [27–29]. These contradictory findings stress the need to investigate and pinpoint the organisational features essential to enhancing industrial performance [30,31]. Previous studies have called for more research into the topic of BDACs and when and why they improve performance [32,33].

By using a variety of theoretical perspectives [9,11,34], the current research has identified several enablers of strategic agility. The role of business dynamics analysis (BDA) in the development of strategic agility needs to be investigated, in light of the growing importance of data-driven decision making in organisations. In earlier studies, BDA capabilities were categorised as a third-order formative component. This factor was composed of BDA infrastructure flexibility, BDA management capability, and BDA personnel expertise capability [35]. We argue that behaviourally driven adaptation has a significant influence on firm performance through strategic agility, because human behaviour is unpredictable and has a profound influence in determining the effectiveness of strategic operations [17,19,31,36]. In addition, the impact of firm creativity on these connections has not been thoroughly researched.

Prior research argues that big data has significant effects on operations management practices. Another study further argues that although big data analytics has been in use to understand customer intentions/behaviours, the use of analytics for improving sustainable performance is less understood. Previous examination argues that organisations are increasingly investing in IT capabilities. While some researchers have established the link between big data analytics capability and competitive advantage [22,29] and agility and competitive advantage [25,32], little empirical testing of big data analytics and strategic agility and sustainable performance exists. Hence, our study seeks to close this research gap by exploring the influence of big data analytics capabilities on sustainable performance through the mediating role of strategic agility.

Insights derived via big data analysis may give chances for business performance improvements [35]. However, firms must also transform these useful insights into actions. Building on the resource-based and dynamic capabilities approaches, as well as the literature on big data analytics capabilities, this research presents significant theoretical contributions. First, it brings a new mechanism—strategic agility—into the interaction between big data analytics capabilities and sustainable performance. This gives a clearer grasp of how big data analytics skills impact sustainable performance. Second, although prior studies have explored this relationship in the settings of major and established economies, we study the indirect relationship between big data analytics capabilities and sustainable performance, based on the business environment of sectors in emerging nations. Third, we further expand the research by analysing the moderating influence of firm creativity on these relationships. This being the case, the following research issues lie within the scope of this study to investigate:

RQ1: What is the influence of big data analytics capabilities on sustainable performance?

RQ2: Does strategic agility mediate the link between big data analytics capabilities and sustainable performance?

RQ3: Does firm creativity moderate the link between big data analytics capabilities, strategic agility, and sustainable performance?

Important new insights from our research will, it is hoped, add to the existing literature and spark academic discussion about how big data analytics skills affect long-term

performance via strategic agility. We used the RBV's key findings to determine that strategic agility mediates the connection between BDAC and sustainable performance. Our research adds to the canon by identifying BDA as a critical element in determining strategic agility and performance. Few details about strengthening this connection have emerged so far. By noting the importance of creativity and strategic agility, our study fills this knowledge vacuum and offers a possible explanation.

## 2. Literature Review and Hypotheses Development

### 2.1. Dynamic Capabilities View

For the purpose of this research, the model is developed from the viewpoint of dynamic capacities. The firm's ability to integrate, build, and reconfigure internal and external resources/competences to meet and potentially shape a quickly changing business environment is a function of its dynamic capabilities [13,19,37]. The resource base consists of both material and immaterial assets, as well as common skills [23,38]. Core components of dynamic skills are the ability to sense and evaluate opportunities, seize them, and translate them into new forms of action [16,39]. In order for businesses to generate revenue and carry out routine operations, they need what are known as "ordinary capabilities", which are characterised as zero-order capabilities [21,27,40].

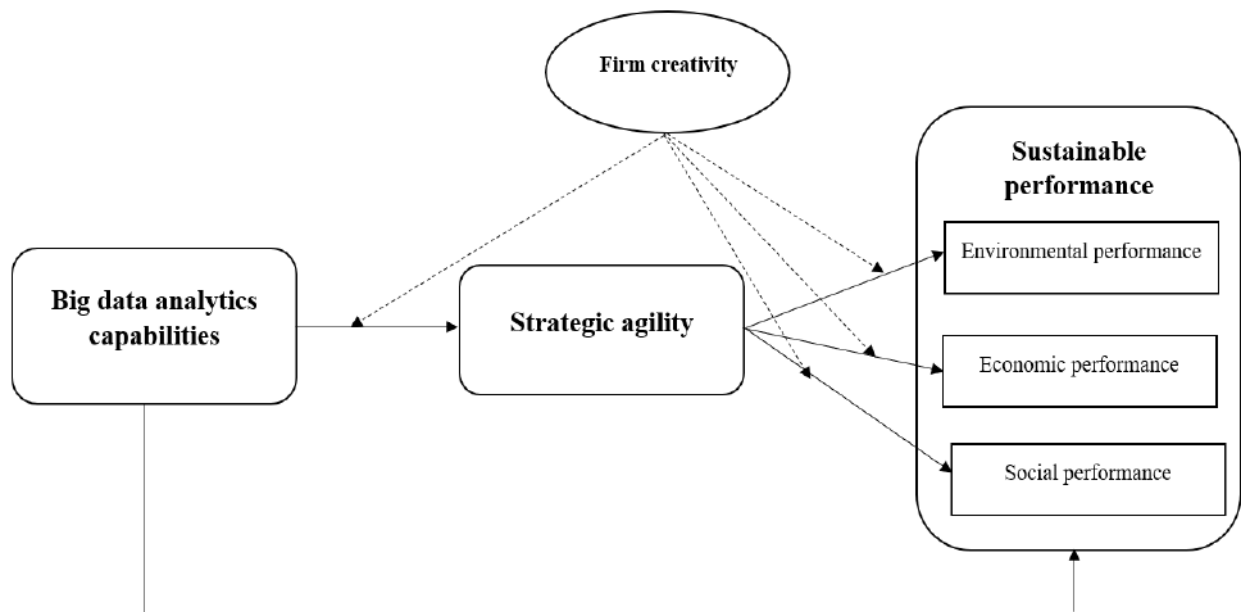
Ordinary capabilities and dynamic capabilities are very different. Companies can function in the present because of their ordinary skills [16,41]. For renewal or reconfiguration, they require dynamic capacities because they are "static" in themselves [11,19,42]. Ordinary talents can be augmented, altered, or even created through the use of dynamic capabilities [43]. Moreover, with dynamic capabilities, businesses can go beyond their usual practices to address new challenges in different contexts [44,45]. Thus, they can produce high-order skills which are focused on the future [46,47]. Nevertheless, even the possession of dynamic qualities does not guarantee that a firm will be successful in the market [11,13,19,48].

Agility encompasses the seeing and acting facets of dynamism [49]. This study proposes a definition of marketing agility which enables businesses to quickly identify and capitalise on market opportunities by adapting their organisational structure and resource allocation in response to shifting demand and intensifying competition. Moreover, "marketing agility pushes organisations to construct their marketing such that these (i.e., their organisational structure and resource allocation) may be adjusted on short notice" [32,39], which is a huge advantage [50]. The consequences of dynamic capabilities on performance may be favourable, negative, or neutral [51]. Hence, dynamic capacities are not synonymous with sustainable performance and stand apart from more conventional abilities. Thus, strategic agility is best inside the framework of dynamic capabilities. Our research model is demonstrated in Figure 1.

### 2.2. Big Data Analytics Capabilities

Recent research has focused on developing a more holistic framework for characterising BDA capabilities. For example, BDA capabilities are defined in prior research as the use, production, and processing of mathematical, statistical, and machine learning tools to deliver analytical reports and actionable insights [52]. Prior research in the Harvard Business Review states that data-driven companies are 6% more profitable and 5% more productive than their competitors [17,34,53]. In addition, a firm's ability to effectively combine its infrastructure, human resources, and management is crucial for the effective implementation of BDA and top-notch financial and operational performance. Yet the managerial challenge, which spans the entire business from top to bottom, is much greater than the technological difficulty of employing big data. In order to meet this issue, it is proposed that businesses place greater emphasis on the following five areas: technology, leadership, decision making, talent management, and corporate culture. Prior studies back the concept of technology, people, and management all working together in a big data

environment and show the importance of an integrated approach to model building, data sourcing, and organisational transformation for reaping the benefits of big data [9,12,54].



**Figure 1.** Research model.

Previous researchers classified BDA capabilities in three distinct groups: BDA technological capabilities, BDA management capabilities, and BDA talent capabilities [1,8,17,55]. There are three phases in the adoption of BDA capabilities: acceptance, assimilation, and routinisation, all of which are embedded in a firm's commitment [56]. They are data integration, analysis, analytical people, prediction, and interpretation. Complementary organisational resources are data governance, evidence-based decision making (EBM), improvisation, and planning for dynamic outcomes. When compared to the other 96% of businesses, those that have capabilities (i.e., the right people, tools, data intention focus, and analytical insights) perform significantly better in both financial and non-financial areas [18,45,57]. For businesses to improve their data analytics skills, they must focus on four key areas: cutting-edge technology and processes, high-quality data, data-savvy employees, and incentives that encourage analytical decision making [23,41,58].

### 2.3. Big Data Analytics Capabilities and Sustainable Performance

Evidence-based decision making has been deemed crucial by several researchers, and there is a favourable correlation between BDA competencies and corporate success. According to prior examination [3], there is a positive and statistically significant correlation between an organisation's IT capability and its financial success. The favourable association between information management skills and company performance was shown to be mediated by the effectiveness of business processes and decision making [11,34,38,59]. In previous studies, business strategy alignment was the focus of an investigation [3,41,60], asking how BDA capabilities moderated the relationship between business strategy and company performance. Using data obtained from Italian companies, an empirical study found that big-data-driven choices have the potential to improve business outcomes [32,61]. Previous examination suggests the following five steps to successfully implement BDA in the healthcare setting: (1) establishing big data governance which refers to the capability of a firm to orchestrate all relevant resources in order to maximise the value of information and insight generation to the organisation; (2) fostering a culture of open information sharing; (3) educating and preparing key personnel to use BDA; (4) incorporating cloud computing into the organisation's BDA; and (5) generating new business ideas [12,34,62].

Previous studies also investigated the favourable correlation between data-savvy teams, data-driven initiatives, and company performance. In addition, writers have pinpointed the tools and methods used by teams who are adept with big data [17,23,63]. Since it is highly improbable that a single expert would be familiar enough with big data, the authors stress the need to build teams with a wide range of expertise in this area. Positive associations between BDA capabilities and creativity were discovered via the mediating influence of dynamic capabilities [64]. Writers also point out how contextual elements such as change, diversity, and antagonism might weaken the connection between BDA and creative output. Organisational culture which uses EBM and promotes the synergistic use of resources leads to significant efficiency improvements in the face of competition. In contrast, previous research on BDA's impact on company performance took a novel tack in constructing a four-domain framework to identify and analyse the factors that might undermine BDA's success at any stage of the process: strategy, culture, technology, and people [37,51,65]. However, companies with rudimentary BDA resources and basic data are more likely to emerge as business failures. Therefore, we suggest the following hypothesis:

**H1:** *Big data analytics capabilities have a significant influence on sustainable performance (i.e., environmental, economic, and social performance).*

#### 2.4. Big Data Analytics Capabilities and Strategic Agility

Prior studies suggested that BDACs allow organisations to manage upheaval and better detect new opportunities [66] and argued that BDACs are closely associated with a company's operational performance [15,23,67]. In their capacity to provide novel insights and tangible business value, BDACs have been emphasised by previous exploration at both the operational and strategic levels. Operational agility is crucial for businesses if they want to adapt effectively to ever-evolving market conditions [45,61,68]. Manufacturing agility is described as "the capacity to shift operational states effectively in response to unpredictable and changing market circumstances" [69]. As stated by prior studies, manufacturing agility enables businesses to see opportunities better and make informed choices [11,27,70]. In line with previous studies, we conceived of agility as a DC that denotes an organisation's capacity to generate novel competences and reconfigure existing ones in response to a shifting environment [71]. In particular, previous studies have shown out that BDA may influence a company's awareness of the need to respond and make swift judgements [21,46,72].

BDACs may help a business to develop greater visibility and to be more nimble [28,43,51,73]. Manufacturing agility is the capacity of a company to swiftly adjust to changes in the market. Previous studies suggested that BDACs are necessary for fostering organisational transformation in this direction [32,51,74]. Nonetheless, organisations with ample BDACs may improve the quality of the data that they use to make decisions [16,44,75]. In line with the established theoretical framework, where researchers have established that organisational BDACs are a strong predictor of DCs [76], BDACs initiate the development of the capacity to accurately forecast market demand, plan for contingency action in response to changing market conditions, rapidly reduce order to delivery cycle times, and thus reduce manufacturing lead times. Thus, we propose the following:

**H2:** *Big data analytics capabilities have a significant influence on strategic agility.*

#### 2.5. Strategic Agility and Sustainable Performance

The term "strategic agility" refers to the value placed on the ability to quickly adjust to new circumstances, including the needs of the market, and the pace at which production lead times may be reduced. Lean manufacturing at its highest level is strategic agility. Past studies have shown a favourable correlation between agility and manufacturing performance [77]. It is reasonable to believe that a business with the potential to be

agile would show better performance results [44,78]. Previous studies have discovered a positive and statistically significant correlation between agility and performance [79]. Agile manufacturing, conceptually speaking, encourages adaptability and rapid response [80]. Since agile manufacturing encourages quick responses from both employees and customers, it is better able to satisfy product and market needs [12,34,81]. The ability to quickly respond to shifts in customer demand, streamline the ordering and shipping processes, and shorten production delays all stem from a company's strategic agility. Previous studies revealed that strategic agility is concerned with boosting the dependability and quality of deliveries [25,63,69,82]. Prior examinations found similar results, confirming a favourable correlation between manufacturing agility and performance [15,67,83]. Previous studies have shown that manufacturing companies that are more agile in the big data environment are better able to optimise their internal processes. Thus, we postulated the following:

**H3:** *Strategic agility has a significant influence on sustainable performance.*

### 2.6. The Moderating Role of Firm Creativity

The effect of creative thinking on innovation effectiveness has been studied. Creativity in the workplace may encourage the skills required to test and implement novel approaches to problem solving [10,12,56,84]. It has been suggested that creativity relates only to the invention of fresh and useful ideas, whereas innovation encompasses both the generation and application of creative ideas [34,51,67,85]. The Critical Thinking Organising Construct (CTOC) was suggested by prior examination and has been extensively discussed in the existing literature [34,86]. Prior studies have also recognised that organisational creativity may have a sizable effect on the DCs of growing businesses [21,87] and that consumer involvement permits a business to address issues in a fresh manner [42,57,88]. In the business world, creativity has been shown to play a crucial role in helping companies grow their innovation capacities and, ultimately, their bottom line [19,65,76,81].

Multifaceted in nature, corporate creativity has always served to generate unique and practical ideas [43,54,67,89]. Prior study indicated that academics should look at the role of organisational creativity in explaining the benefits of agility on performance outcomes [54,67,90]. According to this view, an organisation's capacity to capitalise on opportunities arises from its readiness to adapt to changing conditions by combining and rearranging existing management talent and bringing in new talent and resources [91,92]. To better comprehend and react to shifts in the market, firms' skills allow them to perform tasks and convert their resources more effectively [1,9,63]. Organisational creativity in previous research has been shown to be crucial to many types of nimbleness. Now, researchers have started to examine what goes into an agile performance [93]. For instance, previous studies investigated how inventiveness contributes to the development of business abilities [87,91,93]. They used contingency theory to investigate the effect of an agile organisation on creative output [32,56,94]. Our argument was that, in order for an organisation to be creative, its members must come up with fresh concepts that address pressing issues in the company. Based on our research, we conclude that a company's ability to be creative is a key factor in its ability to expand into new markets and adapt swiftly to changing conditions. Thus, we suggest the following hypotheses:

**H4:** *Firm creativity moderates the link between big data analytics capabilities and strategic agility.*

**H5:** *Firm creativity moderates the link between strategic agility and sustainable performance.*

## 3. Research Methodology

### 3.1. Sampling and Data Collection

A positivist research philosophy was utilised with a quantitative approach to validate the proposed framework, and quantitative data were collected using survey questionnaires to address different levels of the study. The data for our analysis were provided by

Saudi Arabian engineering manufacturers. In order to create a representative sample, we made sure that our respondents came from a broad variety of backgrounds. Our sample businesses were selected from a registry compiled by the Engineering Council of Saudi Arabia (PEC) that has a database of 3610 registered firms.

The initial e-mails were directed to 600 respondents randomly chosen using probability sampling methods (the managers' e-mail addresses were randomly selected by a generated sampling system, such as random-digit dialling (RDD). Of the original 600 businesses, 410 completed and submitted the survey for analysis. Our participants were "production and R&D managers, operations and IT directors, presidents and vice presidents of analytics, and executives in charge of activities such as purchasing, production, operations and planning, and warehousing".

In total, of the 600 companies that took part, 410 submitted forms which were valid for further analysis (response rate of 68%). Most companies had >50 employees (73.2%), with more than five years' experience in the firm (79%), indicating that these organisations have had concerns over their strategic agility, BDACs, creativity, and sustainable performance. Senior managers represented 56%, while general managers who were knowledgeable about the explored issues represented 16.8% (see Table 1).

**Table 1.** Sample composition (N = 410).

Number of employees	<50 (19.5%)
	50–100 (31.5%)
	101–200 (16.8%)
	201–400 (12.5%)
	401–999 (11.5%)
	>1000 (8.2%)
Firm age (years)	<3 (13.5%)
	3–5 (17.5%)
	6–10 (23.5%)
	11–15 (13%)
	>15 (32.5%)
Position	General manager (21.5%)
	Director (16.5%)
	Senior Manager (62%)

Since 410 cases were collected, the current research sample size is a very good and practically acceptable size for the use of structural equation modelling/LISREL. Another test has been conducted using the following equation suggested by Westland [81],  $n \geq 50r^2 - 450r + 1100$ , where  $n$  is the sample size, and  $r$  is the ratio of indicators to latent variables. Since 410 cases were collected, the current research sample size satisfies the lower sample size threshold for structural equation modelling [81].

The manufacturing industry in Saudi Arabia is aggressively seeking to develop its agile manufacturing methods by establishing lean ones, which is why the country's engineering firms were selected for the present study [95]. To put our assumptions to the test, we created a survey to be taken online. We discussed the planned questionnaire and then pre-tested it with 20 academics and businesspeople to make sure before we conducted the survey that it was clear, simple to respond to, and relevant to the sector. Companies were picked at random and sent an e-mail with a link to the online survey together with an explanation of the study's goals. We zeroed in on C-suite executives who were accountable for making decisions in their production divisions and who evaluated matters pertaining to BDA in which they were involved. Our selection criteria for these managerial positions

included an understanding of how business analytics and operational management might be used elsewhere in the company.

### 3.2. Measures

The dimensions of the constructs were measured in this investigation using multi-item scales. Measures on these scales were taken from another study and given a new theoretical framework. A five-point Likert scale was used by the respondents to rate a series of statements, designating 1 to mean “strongly disagree”, while 5 meant “strongly agree”. Sustainable performance (i.e., environmental, social, and economic performance) was measured using a scale adopted from prior research [96–98]. Strategic agility was measured using items from prior studies [99,100]. Big data analytics capabilities were assessed using a scale developed by previous studies [101–103]. Finally, firm creativity was evaluated using a scale adopted in previous examinations [97,104,105].

### 3.3. Common Method Bias Assessment

We took into account the likelihood of shared-method bias, given that the data for independent and outcome variables came from the same source in each company. Like Lindell and Whitney, we used a marker variable (MV) [106]. An MV is a survey question that, in theory, has nothing to do with the other questions and/or should have a negligible effect on any of the other variables in the research. The significance and direction of the observed correlations among the study’s components is modified according to the degree to which the MV correlates with those constructs [107]. The MV’s correlations with the primary variables varied from  $-0.23$  to  $0.09$ , with an average of  $0.04$ . There was no statistically significant difference between them. The common technique bias in this research was mitigated by other factors in addition. One of them was that we used only competent respondents, and the other was that we protected the privacy of all respondents.

## 4. Data Analysis and Results

The suggested model was analysed using structural equation modelling (SEM). Previous studies suggested a two-stage procedure, with a “measurement model” and a “structural model”, and this was followed [108]. The “measurement model” was analysed, and the hypotheses were tested using LISREL 8.8.

### 4.1. Measurement Model

We analysed the reliability and validity of the scale by looking at the correlations between the items. All of the variables had reliability coefficients greater than 0.70. To further evaluate the measures and demonstrate convergent and discriminant validity, a confirmatory factor analysis (CFA) was conducted. The models of canonical factor analysis (CFA) that were performed on theoretically related constructs indicated the results (“Chi-square = 135.62, degrees of freedom = 118,  $p = 0.00$ , CFI = 0.98, GFI = 0.83, TLI = 0.97 and RMSEA = 0.05”), which all point to a close fit with this model. The  $p$ -values for all factor loadings were all below 0.01. The composite reliability measures lay in the 0.693 to 0.891 range, with the average variance extracted (AVE) measurements falling in the 0.57 to 0.81 range (see Table 2). These findings demonstrate convergent validity. Each variable showed more differences from its own block of items than from those of another latent factor (see Table 3). Finally, we examined the discriminant validity using the method suggested by Fornell and Larcker [109] in order to examine the average variance (AVE) extracted for each construct. The overall values were all well above the 0.5 suggested for each construct [109]. Further, the square root of the AVE was larger than the correlation with other constructs [109]. Table 3 shows the square root of the average variance extracted for each construct along the diagonals. It is therefore reasonable to assume all of the scales display discriminant validity.



**Table 2.** Measurement statistics of construct scales.

Construct/Indicators	Indicator Loading	Mean	Standard Deviation	Cronbach's $\alpha$	CR	AVE
Environmental performance (ENP)						
ENP1	0.93	2.12	1.02	0.915	0.946	0.618
ENP2	0.95	2.36	1.16			
ENP3	0.91	3.06	1.34			
ENP4	0.89	2.19	1.45			
Social performance (SOP)						
SOP1	0.88	2.78	1.76	0.901	0.927	0.691
SOP2	0.91	2.29	1.28			
SOP3	0.89	2.81	1.05			
Economic performance (ECP)						
ECP1	0.93	3.12	1.26	0.936	0.971	0.518
ECP2	0.96	2.38	1.08			
ECP3	0.92	2.67	1.25			
ECP4	0.05	3.10	1.20			
Strategic agility (STA)						
STA1	0.89	2.78	1.08	0.910	0.937	0.617
STA2	0.86	2.12	1.26			
STA3	0.94	2.07	1.11			
STA4	0.91	2.75	1.56			
STA5	0.92	3.10	1.20			
Big data analytics (BDAC)						
BDAC1	0.91	2.38	1.26	0.907	0.931	0.680
BDAC2	0.93	2.30	1.20			
BDAC3	0.94	2.12	1.07			
BDAC4	0.90	2.07	1.16			
BDAC5	0.89	2.18	1.25			
BDAC6	0.92	2.76	1.08			
Firm creativity (FRC)						
FRC1	0.95	3.10	1.20	0.926	0.951	0.519
FRC2	0.92	2.36	1.17			
FRC3	0.91	2.19	1.29			
FRC4	0.88	2.41	1.05			

Notes: Factor loading is significant at the 0.001 level; AVE—average variance extracted; CR—composite reliability.

**Table 3.** Discriminant validity of the correlations between constructs.

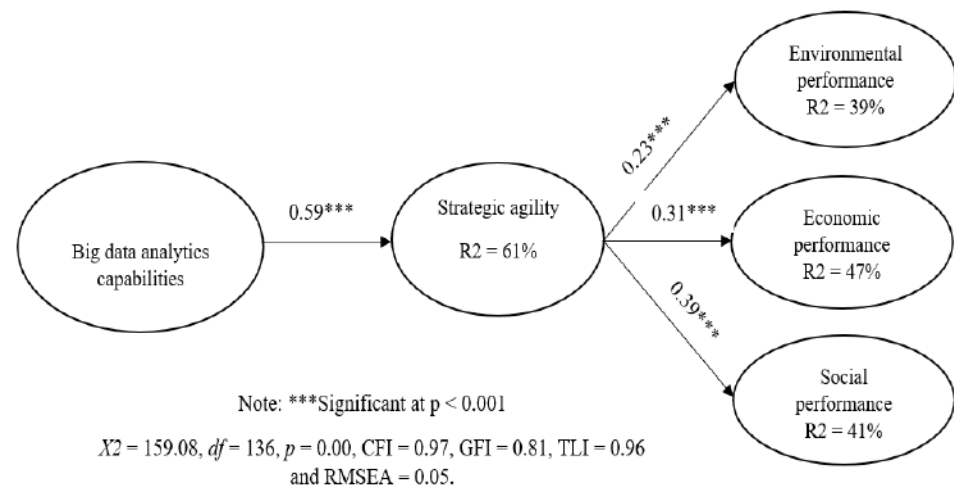
Construct	Correlations and Square Roots of AVE					
	ENP	SOP	ECP	STA	BDAC	FRC
ENP	0.786					
SOP	0.239	0.831				
ECP	0.319	0.328	0.719			
STA	0.418	0.345	0.526	0.785		
BDAC	0.527	0.266	0.418	0.429	0.825	
FRC	0.279	0.518	0.296	0.220	0.418	0.721

#### 4.2. Structural Model Assessment

Evidence of reliability and validity from the assessment of the measurement model allowed us to proceed with testing the predicted links between the research model's components using the structural model [110]. The present study's suggested structural model was tested using a battery of metrics based on the advice of previous studies [111]. As a whole, the model accounted for 61% of the observed variation in strategic agility, 39% in environmental performance, 47% in economic performance, and 41% in social

performance. Hypotheses 1–5 were put to the test using a structural equation model. As can be seen from the data, all of the theorised connections held up.

Our analysis revealed that big data analytics capabilities have a significant influence on sustainable performance (i.e., environmental ( $\beta = 0.23, p < 0.001$ ), social ( $\beta = 0.39, p < 0.001$ ), and economic performance ( $\beta = 0.31, p < 0.001$ )). Thus, H1 was supported. The analysis indicated that big data analytics capabilities have a significant influence on strategic agility ( $\beta = 0.59, p < 0.001$ ). Therefore, H2 was supported. Our study also indicated that strategic agility has a significant influence on sustainable performance (i.e., environmental ( $\beta = 0.43, p < 0.001$ ), social ( $\beta = 0.62, p < 0.001$ ), and economic performance ( $\beta = 0.48, p < 0.001$ )). Thus, H3 was supported. Figure 2 demonstrates our study results.



**Figure 2.** Results of structural equation modelling.

To assess the proposed moderation effect in the structural model, we performed a hierarchical moderation regression analysis in the macro process [112], in line with the recommendations provided by MacKinnon et al. [113]. A significant relationship was found to exist between big data analytics capabilities and firm creativity ( $\beta = 0.29, p < 0.001$ ), strategic agility and environmental performance ( $\beta = 0.31, p < 0.001$ ), strategic agility and economic performance ( $\beta = 0.25, p < 0.001$ ), and strategic agility and social performance ( $\beta = 0.42, p < 0.001$ ). For H4 and H5, our results revealed that the interaction terms contributed to bringing change in the variance explained ( $\text{adj-}R^2 = 0.53; p = 0.001$ ). The interaction term was found to be positive and significant ( $\beta = 0.37; p < 0.001$ ). Therefore, H4 and H5 were supported.

The effect size  $f^2$  developed by a prior study and defined as “the degree to which the phenomenon is present in the population” was also employed to investigate the substantive impact of the study design [114]. Prior examination proposed the use of the numbers 0.02, 0.15, and 0.35 as operational definitions for small, medium, and large impact sizes [114]. With these, our model revealed that strategic agility ( $f^2 = 0.62$ ) and sustainable performance have large effect sizes.

## 5. Discussion and Conclusions

### 5.1. Key Findings

Consistently with other researchers, we concluded that strategic agility strongly mediates the connection between BDACs and sustainable performance [17,23,46,78,90,115]. The Saudi Arabian engineering sector has a growing interest in BDACs to increase firm agility and boost sustainable performance outcomes in the face of fast change brought on by new technologies and increased levels of digitalisation. Our conclusion is understood within this context.

Our study is the first to offer a rigorous empirical test of the distinct effects of big data analytics capability on strategic agility and sustainable performance, which was called

for in previous research [73,81]. Our analysis indicated that strategic agility mediated the relationships between big data analytics capabilities and sustainable performance, which is consistent with prior research in this context [36,51,69].

According to previous examination, innovative businesses obtain deeper insights via data analytics [39,67,81]. Although BDAC is crucial for agility [17,26,45,65,116], no research has looked at the way in which creativity at the company level moderates the connection between BDAC, strategic agility, and long-term success. Our results add to this body of work since they examine how innovation, flexibility, and performance are affected by a company's level of creativity. Hence, engineering companies which foster an environment that rewards original thinking and a can-do attitude amongst its staff are better able to take advantage of BDACs and adapt to shifting market demands. Strategic agility (the ability "to foresee market demand efficiently, minimise order to delivery cycle times, and conduct customisation" [46,81,93] may be improved by manufacturers whose designing is highly inventive and by BDACs. Our research on the moderating and mediating impacts supports the idea that managers' technical competence, especially in the area of goal work, provides a fresh viewpoint on issues and intrinsic motivation, as well as an innovative approach to data analytics.

The study showed that resource-based view and its dynamic capability extension could be successfully used for examining relationships in the development of strategic agility and sustainable performance. The study has further added to the use of dynamic capability theory to understand the evolution of process-oriented capabilities based on big data analytics capabilities. Hence, our study is also a response to the call for exploring the importance of big data analytics capabilities in the development of sustainable performance.

In addition, our results lend credence to BDA as one of the most important determinants affecting long-term performance [6,23,46,79,81,117]. Contrary to the commonly held belief that businesses must rely on the development of tangible resources or capabilities in order to improve their performance and gain a competitive edge, we present evidence that a company's intangible resources help it to develop the capacity to use data analytics, plan better adaptation to changing technological resources, and make quicker decisions [10,26,45,67,83,90,103,118]. Earlier studies have shown that BDACs have a constructive effect on agility [17,26,38,54,119]. In spite of this, there has been a dearth of studies that explore experimentally and in depth how consumer data analysts and organisational creativity affect manufacturing agility and business success.

## 5.2. Theoretical Implications

This research adds significantly to the existing body of knowledge. To begin with, it incorporates the dynamic capabilities viewpoint in order to research the connection between BDACs and strategic flexibility. Despite the fact that the existing research has shown the significance of dynamic skills for BDACs and agility [63,120,121], the manner in which diverse company resources impact on the development of such capabilities has not so far been comprehensively described. Most studies of BDACs to date have used a resource-based perspective to characterise the impact of BDACs on agility. Our conceptual approach adds fresh understanding to the ways in which intangible assets help businesses acquire the skills necessary to become more strategic in their operations. We add to this body of work by specifying the types and quantities of creative resources required by an organisation in order to cultivate such talents to increase its strategic flexibility. Second, although previous works have emphasised the significance of BDACs for firm performance [106,110,122], the mechanisms by which a company's different resources influence the growth of its performance have not been elucidated. In light of prior examinations, scholars should now look at the innovativeness of businesses to understand how strategic flexibility impacts long-term success [28,54,102,123].

Our research adds to the existing body of work that seeks to define and categorise creative thinking in the workplace [16,25,38,59,102,124]. Our research, following prior study, contributes to this line of inquiry by illuminating how firm creativity and BDACs contribute

to strategic agility [104,110,125]. This is important because the prior literature provides little understanding of the way in which organisations develop strategic agility [126]. To add to the problem, we know almost nothing about ways to enhance this effect. Our research is the first to show how BDACs have a more pronounced impact on strategic agility when there is more organisational creativity present. Amabile suggested CTOC in 1997, and it has been discussed extensively in the literature since then [127–133]. Our research on the moderating and mediating roles of creativity in business demonstrates how highly innovative companies are better equipped to reap the benefits of BDACs for long-term performance by adopting more flexible approaches to their operations. Our research also shows that innovative thinking inside businesses helps them adapt to new circumstances and succeed in a highly competitive market. Therefore, strategic agility may aid in the development and capture of fresh ideas for mobilising the resources for seizing corporate value and reconfiguring any current set of resources for value generation.

### *5.3. Practical Implications*

The findings of this research have several applications for manufacturing companies and their executives. First, the research suggests that innovation inside businesses is crucial to long-term success. Managers engaging in creative behaviours, which ensure that their company will be able to transform novel ideas into resources suitable for boosting BDACs, can improve manufacturing lead times, inventory turnover, and procurement lead times. This being so, we propose that manufacturers not only encourage innovation but also provide BDAC education to employees so that everyone can help predict market trends, learn about customers' wants and needs, and quickly develop production strategies with the goal of cutting down on manufacturing lead times.

Second, our research encourages production managers to adopt BDA management approaches and to foster more inventiveness in their businesses as a means of fostering agility. Our research may also help business leaders understand how consumer input is the key to competitive strategic agility. Industrial companies' decision-making processes may be at risk due to a lack of data visualisation skills. A number of earlier studies have identified the inclusion of information from external players as a problematic but crucial part of digital change transition [134–137]. Finally, our research demonstrates to business leaders that consumer participation as data analysts may reveal shifts in market circumstances, allowing them to better adapt their digital transformation initiatives to speed up the fulfilment of orders. Strategically agile businesses should, therefore, prioritise consumer participation in order to maximise value creation.

### *5.4. Limitations and Suggestions for the Future Research*

There are a number of caveats to this study that point to potential future avenues of inquiry. If researchers cannot use cross-sectional data to demonstrate cause-and-effect links, the study's reliability suffers. This gap might be filled by a long-term approach. The focus of the present study is only on long-term effectiveness. Other marketing performance measures, such as sales growth, product launches, customer retention, etc., should also be explored. We hypothesise that additional possible mediators, such as market orientation, learning orientation, and entrepreneurial orientation, might expand the scope of advantages from strategic agility. Only one possible moderator is investigated in this research. Others, such as technical uncertainty, firm size, and industry, may be investigated in further research. In this investigation, the context of the manufacturing sector informed the choice of agility assessment. Future studies will need to make a few adjustments to this metric before they can apply it to the service sector. This would considerably improve our ability to construct theories and comprehend the liminal states of the investigated connections.

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Writing—review & editing, Z.H.A.; Visualization, Z.H.A.; Supervision, M.A. (Mansour Alyahya); Project administration, G.A.; Funding acquisition, M.A. (Mansour Alyahya). All authors have read and agreed to the published version of the manuscript.

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