Article

Sustainable Competitive Advantage Driven by Big Data Analytics and Innovation

Muawia Ramadan [1],*[ID], Hana Shuqqo [1], Layalee Qtaishat [1][ID], Hebaa Asmar [1] and Bashir Salah [2][ID]

[1] Department of Industrial Engineering, Faculty of Engineering and Information Technology, An-Najah National University, P.O. Box 7, Nablus 97300, West Bank, Palestine; hana89shuqqo@gmail.com (H.S.); Layalee.qtaishat@gmail.com (L.Q.); asmar.hebaa@gmail.com (H.A.)

[2] Department of Industrial Engineering, College of Engineering, King Saud University, P.O. Box 800, Riyadh 11421, Saudi Arabia; bsalah@ksu.edu.sa

* Correspondence: mramadan@najah.edu; Tel.: +972-594222198; +970-92345113 (ext. 2370)

check for updates

Abstract: Big data analytics (BDA) is one of the main pillars of Industry 4.0. It has become a promising tool for supporting the competitive advantages of firms by enhancing data-driven performance. Meanwhile, the scarcity of resources on a worldwide level has forced firms to consider sustainable-based performance as a critical issue. Additionally, the literature confirms that BDA and innovation can enhance firms' performance, leading to competitive advantage. However, there is a lack of studies that examine whether or not BDA and innovation alone can sustain a firm's competitive advantage. Drawing on previous studies and dynamic capability theory, this study proposes that big data analytics capabilities (BDAC), supported by a high level of data availability (DA), can improve innovation capabilities (IC) and, hence, lead to the development of a sustainable competitive advantage (SCA). This study examines the proposed hypotheses by surveying 117 manufacturing firms and analyzing responses via partial least squares–structural equation modeling (PLS-SEM) statistical software. Findings reveal that BDAC relies significantly on the degree of DA and has a significant role in increasing IC. Furthermore, the analysis confirms that IC has a significant and direct effect on a firm's SCA, while BDAC has no direct effect on SCA. This study provides valuable insights for manufacturing firms to improve their sustainable business performance and theoretical and practical insights into BDA implementation issues in attaining sustainability in processes.

Keywords: big data analytics (BDA); data availability (DA); dynamic capabilities; firm performance; innovation; strategic management; sustainable competitive advantage (SCA)

1. Introduction

Recently, modern manufacturing systems and advanced technologies have been generating data in greater volumes from a variety of sources in real time, a process referred to as "big data" [1,2]. Businesses today are increasingly utilizing advanced technologies like the Internet of Things (IoT), cyber-physical systems and human–robot collaboration that generate massive amounts of data [3–12].

However, traditional software is incapable of handling such data properly [13]. This is the role of big data analytics (BDA), extracting the value from these data to enhance a firm's competitive advantage [14]. Simply, BDA is the utilization of diverse analytical approaches to handle a variety of large-scale and complex data to extract usable results that serve a firm's performance [15,16].

Despite many studies having validated the significant effect of BDA on firm performance [17–20], many firms are still not certain regarding whether or not to adopt BDA for a variety of reasons. They might lack a sufficient understanding of or capabilities with which to realize its prerequisites or to integrate BDA with their existing processes and systems to extract value [13]. Firms also overlook organizational

aspects of BDA integration, leading to ineffective BDA adoption [21]. In addition, studies in this regard are still lacking and their results are not unified [19,21]. However, global competition and exponential growth in advanced technologies like Internet of Things (IoT), cyber-physical systems and human–robot collaboration [4–12,22] have forced many firms to invest in technologies that considerably enhance their competitive advantage among rivals.

Although firms have invested resources in BDA, many did not attain the maximum strategic benefit because they focused on technological issues and ignored its requirements and strategic role [23]. Therefore, firms must consider other aspects to pursue a data-driven strategy that captures the value of big data [18]. In this regard, many previous studies have considered its managerial and organizational aspects to assist practitioners in effectively exploiting BDA to gain value [24].

One of the most critical issues to address when firms consider adopting BDA is data availability (DA). DA refers to the continuous availability of the required data when and where they are needed [2]. However, some businesses are more critical to DA than others [25]. Thus, storing data on clouds and servers can contribute to DA issues [26,27]. In this regard, all data sources (e.g., systems, devices, machines, sensors, etc.) must be integrated with BDA and connected to the IoT to generate data [28–31]. Moreover, advanced networks, i.e., 5G, are essential in linking data sources with cloud storage systems to ensure real-time DA [32,33].

Another issue to consider is the link between BDA and sustainability, since today, businesses are compelled to base their practices and operations on sustainability (social, environmental, and economic) [25]—in other words, sustainable competitive advantage (SCA). SCA comprises a firm's assets, capabilities and features which are difficult to imitate by competitors [25]. However, to achieve an SCA, firms must effectively utilize their capabilities, i.e., BDA [34,35], where big data analytics capabilities (BDAC) indicate the firm's ability to recognize and analyze different data sources to provide valuable insights [34]. Many researchers have studied the effect of BDA on sustainable firm performance [25,36–38]. Nonetheless, BDA's effect on the environment and its future influence on sustainability is an area for future research [39,40]. Hao et al. [41] conclude that firms' sustainable performance has become a critical success factor. In fact, insufficient big data analytics capabilities (BDAC) and lagging behind the current trend in big data technologies are considerable barriers to SCA [37].

In addition to BDAC, innovation capabilities (IC) are of essential importance in enhancing SCA, where IC indicates a firm's ability to introduce and define innovative ideas and deploy them in designing new products or enhancing the current products [42]. Satupa et al. [42] affirmed that innovation is a key factor in securing competitive advantage. Moreover, many firms consider big data to be a valuable resource that promotes innovation [37,42] which, in turn, leads to competitive advantage [43,44]. Recent literature has posited that creating sustainable new capabilities, like BDA, is necessary for the innovation process because doing so has the potential to support the positive impact of big data on innovation sustainability [41]. Many studies have investigated the role of innovation in firms' performance and competitive advantage [24,42]. Nonetheless, until now, the literature has lacked sufficient evidence clarifying the relationship between BDA, innovative performance and firm performance as an index for its competitive advantage [42].

Most existing BDA studies have focused on its technological aspects; however, there is a lack of studies on BDA in strategic management [21]. Indeed, the gap in the BDA area is multifaceted since the topic is recent and the first publication referring to BDA appeared in 2012 [21]. BDA studies lack multidisciplinary synthesis in exploring the potential value of BDA in the context of strategic management [45]. The importance and role of BDA in an organization's performance lacks sufficient study and the link requires further exploration [19]. In addition, theoretical and empirical research on BDA's effect on firms' performance, considering sustainability, is still lacking [39,46]. Moreover, there is insufficient empirical research on the value extracted from big data for sustainable innovation and firm improvement [41].

Drawing on these identified research gaps, this study aims to propose a strategic conceptual model that considers the effect of DA on BDA and the effect of BDA and IC on SCA. This study also attempts to benefit practitioners by providing an explanation and statistical validation for the proposed model. This study makes many contributions to the field. Firstly, it considers different topics and investigates their roles in attaining SCA; secondly, it provides empirical evidence supporting the extant literature; and thirdly, it considers three diverse aspects of sustainability in one model. Consequently, this study aims to address the following research questions: (1) How does DA affect BDAC? (2) How does BDAC contribute to a firm's IC? (3) How does BDAC enhance a firm's SCA? (4) What is the relationship between IC and a firm's SCA?

2. Research Model and Hypothesis

2.1. Theoretical Model

Figure 1 portrays this study's research model, which consists of four reflective constructs: DA, BDAC, IC and SCA. The model is theorized based on the dynamic capabilities view, in which firms must adapt and innovate their strategic capabilities to cope with the rapid advances and changing trends in the marketplace [47]. This model represents the dynamic capabilities provided by BDAC and IC and is based on the proposition that DA is capable of enhancing firms' sustainable performance, empowered by BDA and innovative processes. Finally, the aforementioned capabilities are proposed to enhance firms' SCA. Table 1 clarifies the constructs' items and their referents.
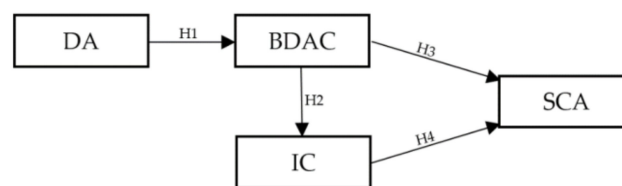

Figure 1. The proposed research model.

Table 1. Model operationalization.

Construct	Item no.	Indicator	Referents
DA	DA1	IT systems, i.e., Enterprise resource planning (ERP) software, are integrated with big data analytics.	[29,31]
	DA2	All devices and sensing machines, e.g., sensors, mobiles, RFID, etc., are connected to the IoT to generate big data.	[48,49]
	DA3	Backup system for big data is effective.	[28,30]
BDAC	BDAC4	Continuously examine innovative opportunities for the strategic use of business analytics.	[18,24,50]
	BDAC5	Enforce adequate plans for the utilization of business analytics.	[18,24,50]
	BDAC6	Perform business analytics planning process in systematic ways.	[18,24,50]
	BDAC7	Frequently adjust business analytics plans to better adapt to changing conditions.	[18,24,50]
IC	IC8	Apply new technologies to the firm's processes.	[51,52]
	IC9	Continuously introduce new products.	[51,52]
	IC10	Use the latest technologies in products.	[51,52]
	IC11	Adopt innovativeness in marketing and promotion.	[51,52]
SCA	SCA12	Average ROS (return on sales) is higher than other competitors.	[14,24,53,54]
	SCA13	Procedures, that help ensure the health and safety of employees, are better than other competitors.	[44,55]
	SAC14	Reward system for employees is better than other competitors.	[53,55]
	SCA15	Superiority in reducing and recycling waste compared to other competitors.	[53,55]

2.2. Research Hypothesis 1: DA as a Prerequisite for BDAC

BDAC is a dynamic capability since it possesses the characteristics of dynamic capabilities, e.g., repeatability, which create an experience that is difficult to imitate and thus create valuable assets that enhance competitive advantage [56]. However, to extract value from BDA, data must be available; a lack of data can be critical to overall performance and, hence, competitive advantage [57]. In addition, lost data cannot be recovered after being identified [49]. Therefore, firms aim to maximize the availability of their data to enhance their BDAC [58] by addressing related issues, such as data source, size and collection method [57].

Advanced Industry 4.0 based manufacturing technologies like cyber-physical systems and human–robot collaboration with sensing devices, e.g., depth camera, proximity sensors, radio frequency identification (RFID), etc., can connect to the IoT to generate big data [4–12,29,31] that can be connected to the cloud to ensure DA [26]. In addition, management information systems, such as enterprise resource planning (ERP), can be integrated with BDA [28,30]. In this regard, advanced wireless networks are supposed to support real-time DA, e.g., 5G [32,33]. However, DA is an essential factor that contributes to the effectiveness of BDA [59]. Therefore, since higher DA promotes better data analytics, we propose that DA is an enabler of BDAC. Hereafter, we propose the following hypothesis:

Hypothesis 1 (H1). *Higher DA can positively enhance BDAC.*

2.3. Research Hypothesis 2: BDAC as an Enabler of IC

BDA has high potential in promoting innovation in products, processes and markets since it provides advanced decision-making prospects [60,61]. BDAC triggers firms to leverage big data, boosting innovation and firm development [41], via enabling novel solutions and rapid adaptation to changes and challenges on a pseudo-real-time basis [62]. In this regard, Erevelles et al. affirmed that BDAC assists firms in creating innovative opportunities [37]. For instance, firms can utilize their customers' big data to innovate their products and services [63]. Moreover, Niebel et al. confirmed that the use of BDAC stimulates firms' tendencies to innovate their products, processes and solutions [60].

Firms can utilize BDA in different data sources, e.g., customer analysis, processes and equipment monitoring, etc. [14,64], to enhance their IC in products, processes and markets [51,52]. In addition, BDAC can facilitate the routine processes and efforts exerted by an innovation team, thus enhancing IC [41]. Moreover, Mikalef et al. [65] proved that BDAC has a positive influence on IC. Therefore, we propose the following hypothesis:

Hypothesis 2 (H2). *BDAC have a positive effect on IC.*

2.4. Research Hypotheses 3 and 4: The Role of BDAC and IC in Enhancing SCA

Both capabilities—BDA and innovation—allow firms to renovate and reconfigure their resources [56]. Breznik et al. [66] also concluded that IC can be considered as both a part and a result of the dynamic capabilities that a firm possesses and that both capabilities contribute to the development of a firm's SCA. BDA permits data-driven decision-making that creates novel ways to innovate and learn how to create value, thus improving a firm's sustainable performance [67]. Consequently, we aim to examine the effects of both capabilities on a firm's SCA.

Firstly, BDAC represents a key source of knowledge creation [64]. This is attained by exploiting different data sources, e.g., production, processes and customers, to support firms in making better decisions, enhancing performance and, thus, sustaining competitive advantage [24]. For instance, Dubey et al. found a significant effect of BDA on a firm's environmental and social sustainability [39]. Additionally, Côrte-Real et al. examined the significant impact of BDA on firms' financial performance. Secondly, innovation as a dynamic capability plays a crucial role in increasing sales, profits and performance excellence through product and process development [68]. Moreover, innovativeness that creates faster adaption to market changes encourages the creation of competitive advantage [42].

Thus, IC contributes significantly to firm performance and competitiveness [69,70]. Both dynamic capabilities, i.e., BDA and innovation, assist firms in overcoming external challenges and competencies by enhancing and sustaining their competitive advantage and overall performance [38,42]. Consequently, we propose the following hypotheses:

Hypothesis 3 (H3). *As a dynamic capability, BDAC has positive effect on firms' SCA.*

Hypothesis 4 (H4). *As a dynamic capability, IC has positive effect on firms' SCA.*

2.5. Sustainable Competitive Advantage (SCA)

Competitive advantage is attained when a firm becomes superior in its success as compared to its current or potential competitors [14]. Moreover, advanced technologies, like BDA, are enablers of sustainable performance by promoting data-driven performance [36]. However, a firm's performance index, compared to its competitors, is a widespread way to indicate competitive advantage [14,44,71]. Thus, to be consistent with this conceptualization, we operationalize the SCA construct to function as a measure for superior performance compared with competitors [71] in terms of social, environmental and economic performance. Therefore, based on previous studies that provide the competitive advantage construct, this construct is the first that constitutes the three aspects of sustainability on the firm level.

3. Research Methodology

3.1. Survey Design

A web-based questionnaire was designed to test the research model and hypotheses. The questionnaire included 15 questions, all rated by respondents on a five-point Likert scale from "1: strongly disagree" to "5: strongly agree". The questionnaire was developed based on the previous literature. The questions were used to establish multi-item reflective measures for the four constructs of the research model. The minimum sample size, determined by G*Power 3.1 software, was 117 samples. Given this, the values for significance level, power and effect size were set to 5%, 90% and 0.3, respectively.

3.2. Data Collection and Analysis Method

This study targeted manufacturing companies from different industrial sectors who were familiar with and had some experience in Industry 4.0 technologies to test the hypotheses. The study did not include the service sectors, since some questions were specifically developed for manufacturing sectors. In addition, the questionnaire aimed to collect data as a primary source to test the hypotheses of the model's constructs. Respondents, members of upper-level management, were targeted to fill out the questionnaire to increase the credibility of the gathered data. This study used partial least squares–structural equation modeling (PLS-SEM) as a statistical software tool for data analysis to test our hypotheses because of its powerful capability in analyzing small sample sizes and its efficiency in analyzing mediating variables and indirect relationships [72]. SmartPLS can be also directly used for the assessment of convergent validity, discriminant validity and reliability. It has a very user-friendly interface and it has very attractive graphical outputs. Its output is very flexible compared to other software packages.

4. Results

PLS-SEM software analyzes the conceptual model in two steps: first, by assessing the measurement model (see Figure A1); second, by assessing the structural model (see Figure A2). The results and explanations of both steps are detailed in the following two sub-sections.

4.1. The Measurement Model: Reliability and Validity Analysis

Reliability and validity tests of the constructs should be conducted to assess the reflective measurement models [73]. Both tests are prerequisites to structural model assessment [74]. These tests aim to assess the internal consistency of the values recorded by the respondents by examining each variable versus its related indicator's values and the validity of the questionnaire's questions. The internal consistency, i.e., reliability, was assessed via Cronbach's alpha (CA) and composite reliability (CR) tests, while the validity was assessed by convergent and discriminant validity tests [72].

Cronbach's alpha is used to measure the internal consistency of a construct's items [75]. The reliability of items/factors must be 0.60 or higher. In addition, the composite reliability, which is used to double-check the internal consistency, should have values above 0.7 [76]. The results are reported in Table 2, which indicates that all constructs are reliable since their corresponding Cronbach's alpha values are above 0.6 and their composite reliability values are higher than 0.7. Therefore, the results affirm that the internal consistency of all constructs is reliable and acceptable.

Table 2. Results of reliability and validity.

Construct	R^2	CA	CR	AVE
DA		0.639	0.804	0.580
BDAC	0.168	0.743	0.837	0.564
IC	0.241	0.711	0.818	0.531
SCA	0.440	0.743	0.839	0.567

Convergent and discriminant validity tests were used to assess the correlation between each construct and its related items [77]. Convergent validity is measured by the average variance extracted (AVE) for all constructs' items with a minimum acceptable value of 0.50. This value indicates that the construct explains 50% or more of the variance of its items [76]. The results reported in Table 2 indicate that all AVE values are above 0.5, thus confirming convergent validity.

Discriminant validity is measured by calculating the square root of all constructs' AVE and comparing the resulting value for each construct with other constructs. Hence, when the correlations within each construct exceed the correlations with all other constructs, the discriminant validity is accepted [78]. The results in Table 3 indicate that the discriminant validity is acceptable.

Table 3. Discriminant validity check (square root of the AVE, shown on the diagonal in bold).

		1	2	3	4
1	**BDAC**	**0.75**			
2	**DA**	0.41	**0.76**		
3	**IC**	0.49	0.33	**0.73**	
4	**SCA**	0.4	0.23	0.66	**0.75**

In addition, the Heterotrait–Monotrait ratio (HTMT) test was used to double-check the discriminant validity; it measures the degree of differences between overlapping constructs. Accepted values range between zero and one and values less than one indicate good reliability [79]. The HTMT values for this study are below 0.90, as shown in Table 4; therefore, discriminant validity is confirmed.

Table 4. HTMT values.

	BDAC	DA	IC	SCA
BDAC				
DA	0.56554			
IC	0.62260	0.48970		
SCA	0.53015	0.32422	0.87068	

Table 5 depicts the PLS estimation of the factor outer loadings of the reflective indicators. Acceptable values are equal to 0.7 or higher for outer loadings [80] or are lower than 0.7 but above 0.4 if the indicator has been recently established [81]. It is essential to check the outer model by testing the *t*-statistics with values above 1.96 to confirm that the outer model loadings are highly significant. Thus, according to the outer loading and *t*-test values, the indicators are highly significant.

Table 5. Estimation of the outer model.

Construct	Item No.	Outer Loading	*t*-Test
DA	DA1	0.664	6.020
	DA2	0.75	7.788
	DA3	0.858	15.355
BDAC	BDAC4	0.819	18.964
	BDAC5	0.693	9.337
	BDAC6	0.748	12.089
	BDAC7	0.738	13.466
IC	IC8	0.689	10.676
	IC9	0.784	15.565
	IC10	0.668	7.844
	IC11	0.766	12.502
SCA	SCA12	0.626	6.315
	SCA13	0.781	16.941
	SAC14	0.807	18.601
	SCA15	0.786	18.089

4.2. Structural Model

The coefficient of determination (R^2) is a statistical value that explains the amount of endogenous construct variance that is explained by the exogenous constructs, with acceptable values between zero and one [76]. The R^2 value for SCA is 0.440, depicted in Table 2, which implies that 44.0% of the variance in the SCA constructs is explained by the BDAC and IC constructs. In addition, PLS-SEM was used to calculate the bootstrapping procedure for assessing the structural model and to obtain the *t*-values [72], as shown in Table 6.

Table 6. Results of the model fit.

	B-Value	STDEV	*t*-Value	*T* Statistics	*p*-Value
H1	0.41	0.078	5.256	5.238	0
H2	0.491	0.081	6.062	6.06	0
H3	0.106	0.09	1.178	1.183	0.237
H4	0.605	0.068	8.897	8.922	0

It is significant to verify the path coefficient values and statistical significance of the relationships between the latent variables in the structural model to evaluate the proposed hypotheses. This verification is performed by assessing the standardized path coefficients (*B*-value), with values equal to or above 0.1 [80], and the associated t-value, having values above 1.96 or below −1.96 at a 0.05 level of significance, i.e., *p*-value [82].

The results of the model fit, provided in Table 6, confirm that DA has a significant and positive impact on BDAC (*B*-value = 0.410, *t*-value = 5.256) and that BDAC has a significant impact on IC (*B*-value = 0.491, *t*-value = 6.062) and is not significant on SCA (*B*-value = 0.106, *t*-value = 1.178). IC has a positive and significant impact on SCA (*B*-value = 0.605, *t*-value = 8.897). However, according to the results, IC has the strongest effect on SCA (0.605). Moreover, the results given in Table 6 confirm that H1, H2 and H4 are supported. However, the relation between BDAC and SCA is not supported.

5. Discussion

The purpose of this study was to investigate the influence of BDA and innovation as dynamic capabilities on firms' SCA. The empirical results demonstrate that BDAC has a significant effect on IC and that IC enhances SCA but BDA capabilities do not. The outcome of this study makes several contributions to the existing body of knowledge in this field. Specifically, this study is the first to explore the effect of DA level on BDAC and the role of BDAC and IC in attaining SCA.

Our findings prove that an increase in DA level positively affects BDAC; the results of the conceptual model support H1. Indeed, when a firm's system is integrated with BDA—all components are connected to IoT, and backup system is effective—the availability of data will increase, which, in turn, will enhance BDAC. However, the BDAC will not be enhanced if the DA in the manufacturing companies is not supported with IoT technology enablers.

In addition, an increase in BDAC has a positive effect on IC, so the results of the model support H2. Therefore, firms implementing BDA are more innovative than others that do not [60]. This result is consistent with the findings of Mikalef [66] and Lozada [83]. Moreover, an increase in IC has a positive effect on SCA, so the results of this study support H4. This result confirms the findings of many similar studies [14,42,84]. In practice, these results are obtained when a firm continuously utilizes new and up-to-date technologies in processes, introduces new products, uses the latest technologies in its products or adopts innovativeness in marketing and promotion. Additionally, the results emphasize that BDAC has a key role in enhancing IC by prompting a firm to adopt the latest technologies in products and processes, introduce new products and innovate in marketing and promotion. In this regard, if the manufacturing companies did not support the BDAC variables, the ability of the companies to cope with the rapid advancements in technologies and market changes will be reduced. Furthermore, whilst reviewing the related literature, we observed that very few studies investigated the BDAC effect on firm SCA. The only study found, to the extent of our review, was a study published in 2020 by Kamble et al. [36], which was conducted at the supply chain level in the agriculture industry and concluded that BDAC is an enabler of sustainable performance. Moreover, no other study has previously investigated the role of DA in reinforcing BDAC. Therefore, this study is the first in conceptualizing the DA construct and synthesizing the SCA construct at the firm level.

In practice, this model is applicable and very efficient in highly customized and technologically advanced production environments where massive amounts of data are generated. Therefore, this model is not useful when it is employed in traditional mass production systems where no highly customized products are needed and the big data will not benefit the producers compared with amount of investment in this filed. In addition to this, the model is not applicable when firms do not have an IT system or enough flexibility to adapt to a wide range of market requirements or to respond to all customer requirements. In such cases, the BD and BDAC may not impact the IC and thus the SCA will not be enhanced. The same can be considered for companies of low competition or market monopoly.

Finally, this study examines DA issues, e.g., network requirements, as a prerequisite for BDA. In addition, this study assists managers in deciding where to invest and allocate resources, focusing on dynamic capabilities as essential enablers for SCA at the firm level in the manufacturing industry.

6. Limitations and Future Research Directions

This study provides valuable insights for manufacturing companies to improve sustainable competitive advantage as well as theoretical and practical insights into BDA implementation issues in attaining sustainability in processes. However, this study has its own limitations and weaknesses, which can be considered as future research opportunities. For example, the research questions of this study have been developed for different types of manufacturing companies in industrial sectors and it was not a sector-based study; Therefore, analyzing the differentiation between different industrial sectors would be inaccurate. Moreover, the service sector was out of the scope of this study and the findings of this study cannot be generalized to the service sectors. This is because the service sector has its own variables which cannot be measured through the same research questions of this study.

Although the sample size was enough to make decisions about the relationships between hypotheses using SmartPLS, for more precise results, it needs to be increased. Moreover, the size of the surveyed manufacturing companies was not taken into consideration in the study, which may impact the findings of the model. As BDA is one of the major pillars of Industry 4.0, the study lacks a real-world case study that explains the implementation of BDA within the Industry 4.0 system. These aspects should be considered as future research directions.

7. Conclusions

In answering the research questions introduced by this study, the results confirm that DA has a significant influence on BDAC, which, in turn, has a significant role in enhancing the relationship with IC. On the other hand, BDAC does not have a significant role in enhancing a firm's SCA. In addition, the results indicate that IC is a significant mediator in the BDAC and SCA relationship. Thus, managers can enhance a firm's SCA by investing in innovation; this might put the firm at the top in rivalries. In addition, they also should be aware of the prerequisites of and issues with BDA implementation.

A firm can make decisions based on the findings of each hypothesis. For example, in H1, since DA has a significant and positive effect on BDAC, firms must digitize all firm levels, i.e., enterprise, operational and manufacturing, to enhance data availability for BDA. At the manufacturing level, firms can digitalize their manufacturing systems by connecting smart entities such as machines, products, tools and devices to the IoT system, which in turn provides a stream of data to BDA. Moreover, firms will lose the benefits of horizontal and vertical connectivity if they do not employ a proper backup system for their generated BD.

H2 confirms that BDAC have a significant and positive role in enhancing firms' IC since continuous examination of the generated BD allows firms to enhance the main pillars of the innovation process, which are product, processes, market and organization innovation. Thus, BDAC maintains the firms' awareness of new technologies to which they must adapt in order to enhance their processes and products and thus be able to distinguish themselves among other competitors in the market. It is concluded that BDAC will enhance innovation management capabilities in manufacturing companies.

In H3, it is found that BDAC as a dynamic capability has positive effect on firms' SCA. Our results have not shown a significant effect of BDAC on firms' SCA. This result is justifiable; BDAC do not ensure that firms will implement the analyzed data and the available reports in the three aspects of sustainability.

As a dynamic capability, IC in H4 has a positive and significant effect on firms' SCA. This encourages the decision-makers to invest in technologies where the innovation capabilities are enhanced. This will reinforce the competitive edge of the firm.

Clearly, using BDA as an advanced analytical tool would be supportive of firms' managerial decision-making, as posited by [85]. The adoption of BDAC in a firm offers several opportunities for improving the IC of firms in the manufacturing industry.

This study proposes a beneficial framework that handles many topics such as DA, BDAC, IC and their roles in reinforcing the SCA of manufacturing firms. However, there is still room for further improvement; for example, the approach of this study limits the generalization of findings to the service sector. Therefore, a possible future work could be a sector-based study approach (i.e., either industrial or service sectors), where more specific variables can be added to the research questions to address specific variables in each sector and thus more accurate results could be obtained and sector differentiation could be precisely analyzed.

Author Contributions: Conceptualization, M.R. and H.S.; methodology, H.S., L.Q., and H.A.; software, H.S., H.A., and L.Q.; validation, M.R., H.S., L.Q., and H.A.; formal analysis, H.S., L.Q., and H.A.; investigation, H.S.; resources, H.S., L.Q., and H.A.; data curation, H.S., L.Q., and H.A; writing—original draft preparation, H.S., L.Q., and H.A.; writing—review and editing, M.R. and B.S.; visualization, M.R.; supervision, M.R.; project administration, M.R. and B.S.; funding acquisition, B.S. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.
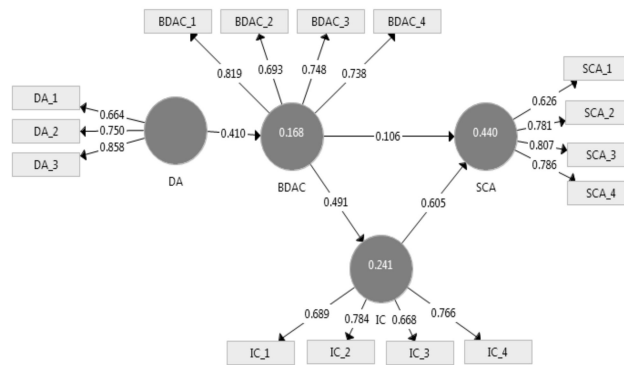
Appendix A

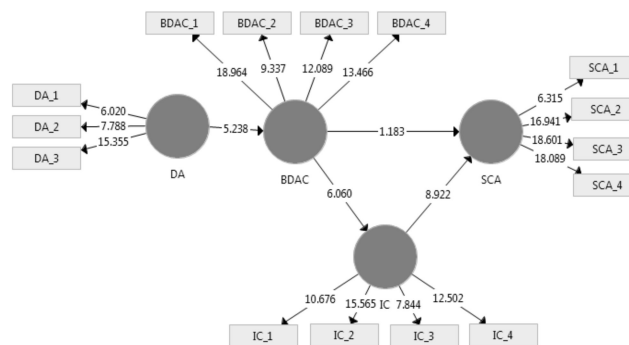**Figure A1.** PLS path modeling estimation of the research model.

Figure A2. Model fit estimation using bootstrapping procedures.

References

1. Kuo, Y.; Kusiak, A. From data to big data in production research: The past and future trends. *Int. J. Prod. Res.* **2018**, *57*, 4828–4853. [CrossRef]
2. Jin, X.; Wah, B.W.; Cheng, X.; Wang, Y. Significance and Challenges of Big Data Research. *Big Data Res.* **2015**, *2*, 59–64. [CrossRef]
3. Manavalan, E.; Jayakrishna, K. A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. *Comput. Ind. Eng.* **2019**, *127*, 925–953. [CrossRef]
4. Roy, S.; Edan, Y. Investigating Joint-Action in Short-Cycle Repetitive Handover Tasks: The Role of Giver Versus Receiver and its Implications for Human-Robot Collaborative System Design. *Int. J. Soc. Robot.* **2018**, 1–16. [CrossRef]
5. Michalos, G.; Makris, S.; Tsarouchi, P.; Guasch, T.; Kontovrakis, D.; Chryssolouris, G. Design Considerations for Safe Human-robot Collaborative Workplaces. *Procedia CIRP* **2015**, *37*, 248–253. [CrossRef]
6. Someshwar, R.; Edan, Y. Givers & receivers perceive handover tasks differently: Implications for human-robot collaborative system design. *arXiv* **2017**, arXiv:1708.06207.
7. Tsarouchi, P.; Matthaiakis, A.-S.; Makris, S.; Chryssolouris, G. On a human-robot collaboration in an assembly cell. *Int. J. Comput. Integr. Manuf.* **2016**, *30*, 580–589. [CrossRef]
8. Someshwar, R.; Meyer, J.; Edan, Y. Models and Methods for H-R Synchronization. *IFAC Proc. Vol.* **2012**, *45*, 829–834. [CrossRef]
9. Tsarouchi, P.; Michalos, G.; Makris, S.; Athanasatos, T.; Dimoulas, K.; Chryssolouris, G. On a human–robot workplace design and task allocation system. *Int. J. Comput. Integr. Manuf.* **2017**, *30*, 1272–1279. [CrossRef]

10. Someshwar, R.; Meyer, J.; Edan, Y. A Timing Control Model for H-R Synchronization. *IFAC Proc. Vol.* **2012**, *45*, 698–703. [CrossRef]

11. Michalos, G.; Makris, S.; Spiliotopoulos, J.; Misios, I.; Tsarouchi, P.; Chryssolouris, G. ROBO-PARTNER: Seamless Human-Robot Cooperation for Intelligent, Flexible and Safe Operations in the Assembly Factories of the Future. *Procedia CIRP* **2014**, *23*, 71–76. [CrossRef]

12. Tsarouchi, P.; Makris, S.; Michalos, G.; Stefos, M.; Fourtakas, K.; Kaltsoukalas, K.; Kontrovrakis, D.; Chryssolouris, G. Robotized Assembly Process Using Dual Arm Robot. *Procedia CIRP* **2014**, *23*, 47–52. [CrossRef]

13. 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]

14. 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]

15. Lamba, H.S.; Dubey, S.K. 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) (Trends and Future Directions), Noida, India, 2–4 September 2015; pp. 1–6.

16. Müller, O.; Junglas, I.; Brocke, J.V.; Debortoli, S. Utilizing big data analytics for information systems research: Challenges, promises and guidelines. *Eur. J. Inf. Syst.* **2016**, *25*, 289–302. [CrossRef]

17. 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.* **2016**, *55*, 5011–5026. [CrossRef]

18. 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]

19. Anwar, M.; Khan, S.Z.; Shah, S.Z.A. Big Data Capabilities and Firm's Performance: A Mediating Role of Competitive Advantage. *J. Inf. Knowl. Manag.* **2018**, *17*, 1850045. [CrossRef]

20. Al-Sai, Z.A.; Abdullah, R.; Husin, M.H. Big Data Impacts and Challenges: A Review. In Proceedings of the 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), Amman, Jordan, 9–11 April 2019; pp. 150–155. [CrossRef]

21. Mikalef, P.; Pappas, I.O.; Krogstie, J.; Giannakos, M. Big data analytics capabilities: A systematic literature review and research agenda. *Inf. Syst. E Bus. Manag.* **2017**, *16*, 547–578. [CrossRef]

22. Sharma, R.; Mithas, S.; Kankanhalli, A. Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. *Eur. J. Inf. Syst.* **2014**, *23*, 433–441. [CrossRef]

23. Grover, V.; Chiang, R.H.L.; 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]

24. 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]

25. Raut, R.D.; Mangla, S.K.; Narwane, V.S.; Gardas, B.B.; Priyadarshinee, P.; Narkhede, B.E. Linking big data analytics and operational sustainability practices for sustainable business management. *J. Clean. Prod.* **2019**, *224*, 10–24. [CrossRef]

26. Aldossary, S.; Allen, W. Data Security, Privacy, Availability and Integrity in Cloud Computing: Issues and Current Solutions. *Int. J. Adv. Comput. Sci. Appl.* **2016**, *7*, 485–498. [CrossRef]

27. Wang, X.; Yang, L.T.; Liu, H.; Deen, M.J. A Big Data-as-a-Service Framework: State-of-the-Art and Perspectives. *IEEE Trans. Big Data* **2017**, *4*, 325–340. [CrossRef]

28. Cadersaib, B.Z.; Ben Sta, H.; Rahimbux, B.A.G. Making an Interoperability Approach between ERP and Big Data Context. In Proceedings of the 2018 Sixth International Conference on Enterprise Systems (ES), Limassol, Cyprus, 1–2 October 2018; pp. 146–153. [CrossRef]

29. Mourtzis, D.; Vlachou, E.; Milas, N. Industrial Big Data as a Result of IoT Adoption in Manufacturing. *Procedia CIRP* **2016**, *55*, 290–295. [CrossRef]

30. Babu, M.S.P.; Sastry, S.H. Big data and predictive analytics in ERP systems for automating decision making process. In Proceedings of the 2014 IEEE 5th International Conference on Software Engineering and Service Science, Beijing, China, 27–29 June 2014; pp. 259–262.

31. Syafrudin, M.; Alfian, G.; Fitriyani, N.L.; Rhee, J.T. Performance Analysis of IoT-Based Sensor, Big Data Processing, and Machine Learning Model for Real-Time Monitoring System in Automotive Manufacturing. *Sensors* **2018**, *18*, 2946. [CrossRef]

32. Zhang, N.; Yang, P.; Ren, J.; Chen, D.; Yu, L.; Shen, X. Synergy of Big Data and 5G Wireless Networks: Opportunities, Approaches, and Challenges. *IEEE Wirel. Commun.* **2018**, *25*, 12–18. [CrossRef]

33. Furqan, M.; Zhang, C.; Yan, W.; Shahid, A.; Wasim, M.; Huang, Y. A Collaborative Hotspot Caching Design for 5G Cellular Network. *IEEE Access* **2018**, *6*, 38161–38170. [CrossRef]

34. Hu, F.; Liu, W.; Tsai, S.-B.; Gao, J.; Bin, N.; Chen, Q. An Empirical Study on Visualizing the Intellectual Structure and Hotspots of Big Data Research from a Sustainable Perspective. *Sustainability* **2018**, *10*, 667. [CrossRef]

35. Shamim, S.; Zeng, J.; Shariq, S.M.; Khan, Z. Role of big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. *Inf. Manag.* **2019**, *56*, 103135. [CrossRef]

36. Kamble, S.S.; Gunasekaran, A.; Gawankar, S.A. Achieving sustainable performance in a data-driven agriculture supply chain: A review for research and applications. *Int. J. Prod. Econ.* **2020**, *219*, 179–194. [CrossRef]

37. Erevelles, S.; Fukawa, N.; Swayne, L. Big Data consumer analytics and the transformation of marketing. *J. Bus. Res.* **2016**, *69*, 897–904. [CrossRef]

38. Singh, S.K.; El-Kassar, A.-N. Role of big data analytics in developing sustainable capabilities. *J. Clean. Prod.* **2019**, *213*, 1264–1273. [CrossRef]

39. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Papadopoulos, T.; Luo, Z.; Wamba, S.F.; Roubaud, D. Can big data and predictive analytics improve social and environmental sustainability? *Technol. Forecast. Soc. Chang.* **2019**, *144*, 534–545. [CrossRef]

40. Amui, L.B.L.; Jabbour, C.J.C.; Jabbour, A.B.L.D.S.; Kannan, D. Sustainability as a dynamic organizational capability: A systematic review and a future agenda toward a sustainable transition. *J. Clean. Prod.* **2017**, *142*, 308–322. [CrossRef]

41. Hao, S.; Zhang, H.; Song, M. Big Data, Big Data Analytics Capability, and Sustainable Innovation Performance. *Sustainability* **2019**, *11*, 7145. [CrossRef]

42. Sutapa, S.; Mulyana, M.; Wasitowati, W. The Role of Market Orientation, Creativity and Innovation in Creating Competitive Advantages and Creative Industry Performance. *J. Din. Manaj.* **2017**, *8*, 152–166. [CrossRef]

43. 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]

44. 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]

45. Ardito, L.; Scuotto, V.; Del Giudice, M.; Petruzzelli, A.M.; Messeni, A. A bibliometric analysis of research on Big Data analytics for business and management. *Manag. Decis.* **2019**, *57*, 1993–2009. [CrossRef]

46. El-Kassar, A.-N.; Singh, S.K. Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technol. Forecast. Soc. Chang.* **2019**, *144*, 483–498. [CrossRef]

47. Linden, G.; Teece, D.J. Remarks on Pisano: Toward a prescriptive theory of dynamic capabilities. *Ind. Corp. Chang.* **2018**, *27*, 1175–1179. [CrossRef]

48. Lu, P.; Zhang, L.; Liu, X.; Yao, J.; Zhu, Z. Highly efficient data migration and backup for big data applications in elastic optical inter-data-center networks. *IEEE Netw.* **2015**, *29*, 36–42. [CrossRef]

49. Guo, W.; Qin, S.; Lu, J.; Gao, F.; Jin, Z.; Wen, Q. Improved Proofs Of Retrievability And Replication For Data Availability In Cloud Storage. *Comput. J.* **2020**, *63*, 1216–1230. [CrossRef]

50. Kim, G.; Shin, B.; Kwon, O. Investigating the Value of Sociomaterialism in Conceptualizing IT Capability of a Firm. *J. Manag. Inf. Syst.* **2012**, *29*, 327–362. [CrossRef]

51. Rosli, M.M.; Sidek, S. The Impact of Innovation on the Performance of Small and Medium Manufacturing Enterprises: Evidence from Malaysia. *J. Innov. Manag. Small Mediu. Enterp.* **2013**, *2013*, 1–16. [CrossRef]

52. Udriyah, U.; Tham, J.; Azam, S.M.F. The effects of market orientation and innovation on competitive advantage and business perfor-mance of textile SMEs. *Manag. Sci. Lett.* **2019**, *9*, 1419–1428. [CrossRef]

53. Gunasekaran, A.; Papadopoulos, T.; Dubey, R.; Wamba, S.F.; Childe, S.J.; Hazen, B.; Akter, S. Big data and predictive analytics for supply chain and organizational performance. *J. Bus. Res.* **2017**, *70*, 308–317. [CrossRef]

54. Saeidi, S.P.; Sofian, S.; Saeidi, P.; Saeidi, S.P.; Saaeidi, S.A. How does corporate social responsibility contribute to firm financial performance? The mediating role of competitive advantage, reputation, and customer satisfaction. *J. Bus. Res.* **2015**, *68*, 341–350. [CrossRef]

55. Cantele, S.; Zardini, A. Is sustainability a competitive advantage for small businesses? An empirical analysis of possible mediators in the sustainability–financial performance relationship. *J. Clean. Prod.* **2018**, *182*, 166–176. [CrossRef]

56. Ambrosini, V.; Bowman, C. What are dynamic capabilities and are they a useful construct in strategic management? *Int. J. Manag. Rev.* **2009**, *11*, 29–49. [CrossRef]

57. Libes, D.; Shin, S.; Woo, J. Considerations and recommendations for data availability for data analytics for manufacturing. In Proceedings of the 2015 IEEE International Conference on Big Data (Big Data), Santa Clara, CA, USA, 29 October–1 November 2015; pp. 68–75.

58. Liu, J.; Shen, H. A Low-Cost Multi-failure Resilient Replication Scheme for High Data Availability in Cloud Storage. In Proceedings of the 2016 IEEE 23rd International Conference on High Performance Computing (HiPC), Hyderabad, India, 19–22 December 2016; pp. 242–251.

59. Dombrowski, U.; Wullbrandt, J.; Krenkel, P. Industrie 4.0 in production ramp-up management. *Procedia Manuf.* **2018**, *17*, 1015–1022. [CrossRef]

60. Niebel, T.; Rasel, F.; Viete, S. BIG data—BIG gains? Understanding the link between big data analytics and innovation. *Econ. Innov. New Technol.* **2019**, *28*, 296–316. [CrossRef]

61. Mikalef, P.; Boura, M.; Lekakos, G.; Krogstie, J. Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *Br. J. Manag.* **2019**, *30*, 272–298. [CrossRef]

62. Jeble, S.; Kumari, S.; Patil, Y. Role of Big Data in Decision Making. *Oper. Supply Chain Manag. Int. J.* **2018**, *11*, 36–44. [CrossRef]

63. Story, V.M.; O'Malley, L.; Hart, S. Roles, role performance, and radical innovation competences. *Ind. Mark. Manag.* **2011**, *40*, 952–966. [CrossRef]

64. Chen, D.Q.; Preston, D.S.; Swink, M. How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *J. Manag. Inf. Syst.* **2015**, *32*, 4–39. [CrossRef]

65. Mikalef, P.; Boura, M.; Lekakos, G.; Krogstie, J. Complementarities between Information Governance and Big Data Analytics Capabilities on Innovation. In Proceedings of the European Conference on Information Systems (ECIS), Portsmouth, UK, 23–28 June 2018; p. 149.

66. Breznik, L.; Hisrich, R.D. Dynamic capabilities vs. innovation capability: Are they related? *J. Small Bus. Enterp. Dev.* **2014**, *21*, 368–384. [CrossRef]

67. Fiorini, P.D.C.; Seles, B.M.R.P.; Jabbour, C.J.C.; Mariano, E.B.; de Sousa Jabbour, A.B.L. Management theory and big data literature: From a review to a research agenda. *Int. J. Inf. Manag.* **2018**, *43*, 112–129. [CrossRef]

68. Sulistyo, H. Siyamtinah Innovation capability of SMEs through entrepreneurship, marketing capability, relational capital and empowerment. *Asia Pac. Manag. Rev.* **2016**, *21*, 196–203. [CrossRef]

69. Han, C.; Gao, S. A Chain Multiple Mediation Model Linking Strategic, Management, and Technological Innovations to Firm Competitiveness. *Rev. Bus. Manag.* **2019**, *21*, 879–905. [CrossRef]

70. Sulistyo, H.; Ayuni, S. Competitive advantages of SMEs: The roles of innovation capability, entrepreneurial orientation, and social capital. *Contaduría Admin.* **2019**, *65*, 156. [CrossRef]

71. Schilke, O. On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strat. Manag. J.* **2013**, *35*, 179–203. [CrossRef]

72. Hair, J.F.; Hult, G.T.M.; Ringle, C.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*; SAGE: Thousand Oaks, CA, USA, 2014; Volume 46.

73. Hair, J.F.; Ringle, C.M.; Sarstedt, M. PLS-SEM: Indeed a Silver Bullet. *J. Mark. Theory Pract.* **2011**, *19*, 139–152. [CrossRef]

74. Codita, R. Testing the Contingency Model of Marketing-Mix Standardization and Its Performance Outcomes. In *Contingency Factors of Marketing-Mix Standardization*; Gabler Verlag-Springer Fachmedien Wiesbaden GmbH: Wiesbaden, Germany, 2011; pp. 136–206.

75. Rutkowski, L.; von Davier, M.; Rutkowski, D. Estimating reliability. In *Handbook of International Large-Scale Assessment*; Leslie Rutkowski, D.R., von Davier, M., Eds.; Chapman and Hall/CRC: New York, NY, USA, 2013; p. 647. [CrossRef]

76. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M.; Hair, J.F. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [CrossRef]

77. Morizot, J. Construct Validity of Adolescents' Self-Reported Big Five Personality Traits: Importance of Conceptual Breadth and Initial Validation of a Short Measure. *Assessment* **2014**, *21*, 580–606. [CrossRef] [PubMed]

78. Ab Hamid, M.R.; Sami, W.; Sidek, M.H.M. Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. *J. Phys. Conf. Ser.* **2017**, *890*, 12163. [CrossRef]

79. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2014**, *43*, 115–135. [CrossRef]

80. Cepeda-Carrion, G.; Cegarra-Navarro, J.G.; Cillo, V. Tips to use partial least squares structural equation modelling (PLS-SEM) in knowledge management. *J. Knowl. Manag.* **2019**, *23*, 67–89. [CrossRef]

81. Hulland, J. Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies. *Strateg. Manag. J.* **1999**, *20*, 195–204. [CrossRef]

82. Lorna, U.; Heričko, M.; Ting, I.-H. An empirical studyof the effect of SCM practice on corporate performance. In *Knowledge Management in Organizations*; Lorna Uden, I.-H.T., Heričko, M., Eds.; Springer Cham: Yokohama, Japan, 2015; Volume 224, p. 128.

83. Lozada, N.E.; Arias-Pérez, J.; Perdomo-Charry, G. Big data analytics capability and co-innovation: An empirical study. *Heliyon* **2019**, *5*, e02541. [CrossRef] [PubMed]

84. Aziz, N.N.A.; Samad, S. Innovation and Competitive Advantage: Moderating Effects of Firm Age in Foods Manufacturing SMEs in Malaysia. *Procedia Econ. Financ.* **2016**, *35*, 256–266. [CrossRef]

85. ZareRavasan, A.; Ashrafi, A. An empirical investigation on big data analytics (BDA) and innovation performance. In Proceedings of the 3rd International Conference on Business and Information Management—ICBIM '19, Paris, France, 12–14 September 2019; pp. 97–101. [CrossRef]