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THE NEXUS OF BIG DATA ANALYTICS, KNOWLEDGE SHARING, AND PRODUCT INNOVATION IN MANUFACTURING

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Abstract. In today's highly competitive business environments, manufacturers face stiff competition. As digital technologies have become more pervasive, many businesses in the manufacturing sector have begun to tap into the potential of big data analytics to gain an edge in their markets. Companies in the manufacturing sector can gain a significant competitive advantage by strategically utilizing big data analytics to uncover profound insights that have the potential to significantly enhance their capabilities in product innovation.
This research delves into communication's role as a go-between for big data analytics and product innovations' success at manufacturing firms. The validity and reliability of the measurement scales were first thoroughly examined in this study. The research model was then tested using structural equation modeling and process macro analysis.
The analytical findings unveil those big data analytics exert a pronounced, positive, and statistically significant impact on product innovation performance and information-sharing dynamics. Furthermore, it is discerned that information-sharing exerts a substantial and affirmative influence on the capacity for product innovation. Additionally, it is established that the impact of big data analytics on product innovation performance undergoes moderation by the information-sharing mechanism.

Keywords: big data analytics, product innovation, information sharing, analytics-driven innovation, data analytics in manufacturing, innovation performance.

JEL Classification: M00, O31, D83.

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1. Introduction

The development of computer and internet technologies has eliminated the problem of accessing data, a primary issue 20 years ago. However, the widespread use of information technologies, particularly mobile technologies and social media, has led to the accumulation of vast amounts of data, which is continuing to accelerate (M. Chen et al., 2014). Digital technology has allowed for excessive data storage, making it easy to access large amounts of data (Elgendy & Elragal, 2014). As a result, the amount of data produced, stored, and manipulated has significantly increased, leading to the development of big data and data science (Gürsakal, 2017). This development has made data and its analysis the essential topics in modern science and business (Kalyvas & Albertson, 2015) as data is obtained from various sources. The development of internet technology has resulted in almost all data being produced and processed by internet companies (Sagiroglu & Sinanc, 2013), such as Google, Facebook, Baidu, Taobao, and Alibaba, which process petabytes of data.

Big data's role in modern society is pivotal, as it underpins innovation and competitive prowess in business and science. The advent of technologies like social media and smart devices has led to an unprecedented data deluge, which, when harnessed, can offer companies a competitive edge (Hu et al., 2021). Since the 1990s, knowledge management has been crucial for leveraging expertise to foster innovation and maintain market leadership. In today's global economy, the ability to transform data into actionable knowledge is essential for success in all industries (Tian, 2017). The shift from the "IT Age" to the "Data Age" is marked by a surge in knowledge and technological progress, reshaping human civilization. Big data's influence is profound and wide-reaching, serving as a key strategic asset that drives corporate innovation, competitiveness, and productivity (Su et al., 2022).

Big data analytics (BDA), the management, analysis, and processing of large amounts of data, is becoming a popular topic for practitioners and researchers as it helps organizations improve operational efficiency, strategic direction, customer service, product and service development, and more. Companies must evaluate the effects of BDA capabilities on performance to stay competitive (Bahrami & Shokouhyar, 2021). New technologies like AI, the Internet of Things, and cloud computing have created unprecedented data critical to competitive advantage, business performance, and innovation (Munir et al., 2023). Researchers and practitioners are interested in BDA and management tools to improve efficiency and decision-making. Business managers must adopt new technology to stay competitive and understand customer needs (Saleem et al., 2021). New product innovation relies heavily on mobile devices, social media platforms, and the internet to establish better customer connections and receive feedback faster and cheaper than official surveys (Zhan et al., 2017).

Product Innovation Capacity (PIC) helps to manage organizational knowledge to improve customer service and success. Companies must innovate constantly and involve suppliers to enhance innovation, flexibility, quality, development time, and cost, but it can reduce control over the project if not managed properly (Akroush & Awwad, 2018; Kulangara et al., 2016; Zhan et al., 2017).

Information sharing between companies is crucial in new product development because it allows for better coordination and collaboration among partners, improves communication, and reduces the risk of delays or errors. By sharing information such as product designs, production schedules, and inventory levels, partners can identify and resolve potential issues early on, which can help to speed up the product development process and ensure that the final product meets the needs and expectations of customers (Chen et al., 2021; Wang et al., 2020). Information sharing can lead to more efficient and cost-effective production processes and flexibility and adaptability to changing market conditions (Huo et al., 2021).

Companies with comprehensive market knowledge can integrate various market insights to enhance product innovation. This depth of understanding, encompassing customer and competitor insights, is pivotal for practical innovation and problem-solving. It allows firms to discern complex relationships between customer needs and competitor offerings, fostering the creation of superior products. Companies can foster innovation and develop solutions that resonate with customer needs by empowering employees and customers with the necessary resources and a supportive environment (Wan & Liu, 2021). Regular customer data analysis, including dynamic market segmentation, is crucial for anticipating customer demands, which requires significant resource investment (Fernando et al., 2018). A company's innovative capabilities, defined as the ability to generate and implement new ideas and solutions, are critical for responsiveness to market demands and can significantly influence its competitive stance and growth (Bahrami & Shokouhyar, 2021).

Studies examine the effects of BDA and information sharing on new product development by improving innovation capability. Companies can use BDA to analyze information suppliers share on raw materials and components to identify trends and patterns that can inform new product development or the optimization of existing ones (Sun & Liu, 2021; Tsang et al., 2022). In addition, information sharing between companies can positively impact innovation capability (Jiaxi, 2009). Companies can also use BDA to analyze information shared by customers and other stakeholders to identify new product features or services that meet their needs or preferences.

Advanced BDA capabilities allow a company to gather and analyze diverse data, yielding more precise insights and improving information sharing within the organization and with partners, thus enhancing efficiency and decision-making (Morimura & Sakagawa, 2023; Janssen et al., 2017).

BDA capability can automate data processing tasks and ensure data security. More accurate and comprehensive data inputs can positively impact information sharing and PIC. Therefore, this research aimed to examine the role of information exchange as a mediator between BDA capability and PIC.

The study presents the theoretical framework in Section 2, where we introduce BDA, information sharing, and PIC. In Section 3, we explain the materials and methods used in the study, including the data collection and analysis techniques employed. The findings of the study are presented in Section 4, where the effects of BDA and information sharing on PIC are analyzed. In Section 5, we discuss the implications of these findings for practitioners and researchers, including the potential for increased competitiveness and performance through BDA and effective information sharing. Finally, in Section 6, we summarize the study's key takeaways and identify opportunities for future research.

2. Theoretical framework

2.1. Big data analytics

The concept of BDA has evolved, beginning with the development of large-scale data processing systems in the 1960s and 1970s (Borkovich & Noah, 2014). These early systems were primarily used for scientific and government research. However, as technology has progressed, the availability and affordability of data storage and processing power have increased, making BDA more accessible to organizations of all sizes. With the advent of the internet and the explosion of digital data in the 21st century, BDA has become an increasingly important area of research and development. As a result, various BDA tools and technologies have been developed to handle the volume, velocity, and variety of big data (McAfee et al., 2012).

"Big data" describes the massive amounts of information created and collected daily (Sun & Liu, 2021). This data can come from various sources, including social media, sensors, and transactional systems. The high volume, velocity, and variety of big data make it challenging to process and analyze with conventional data management methods. Data can be categorized into three broad categories: volume (the total amount of data being generated), velocity (how quickly that data is being generated), and variety (the different formats in which that data is being generated, such as text, images, and sound) (Gandomi & Haider, 2015; Intezari & Gressel, 2017; Liedong et al., 2020).

Information is the driving force behind a company's strategic, tactical, and operational decision-making. However, the amount of information and data companies collect rapidly increases, making it difficult for businesses to identify and extract the most relevant information to manage their operations and supply chain. The term "BDA" has emerged in this context, pointing to new opportunities for exploring and utilizing large data sets (Kache & Seuring, 2017).

BDA involves five key steps: data access and storage, preprocessing, integration, analysis, and interpretation, each critical for realizing data's full value (Ye et al., 2021). However, the benefits of BDA are contingent on the governance of processes and structures that dictate the availability and analysis of information, emphasizing the need for strategic resource allocation to enhance business capabilities (Mikalef et al., 2020). BDA applications in business streamline supply chain management by optimizing inventory and forecasting, enhancing performance, and bolstering security through risk analysis (Raman et al., 2018). In manufacturing, BDA aids in boosting efficiency, cutting costs, and enhancing quality control across production stages (Yin & Kaynak, 2015).

BDA can improve product innovation by analyzing data from various sources, such as customer feedback, market research, and competitor analysis. Additionally, it can improve the speed and efficiency of the development process by identifying patterns and trends in development data.

2.2. Information sharing

Information sharing refers to exchanging information among individuals, organizations, or systems. Information sharing between firms refers to exchanging information among different organizations. This process can include sharing knowledge, data, and other information, such as market trends, best practices, and new technologies (Markovic & Bagherzadeh, 2018).

Information sharing is pivotal in enhancing firm performance, fostering innovation, and sharpening competitiveness. It catalyzes organizational collaboration and communication, which are essential for streamlining business processes and facilitating effective product development (Hsu et al., 2008; Huo et al., 2021). By sharing knowledge, expertise, and technology among stakeholders – including customers, suppliers, and employees – firms can leverage resources they lack internally, thereby boosting their competitive edge and performance (Şahin & Topal, 2019). The PIC framework underscores that the exchange of information must be timely, relevant, complete, and accurate, supporting the innovation process, accelerating development times, and improving the success rates of new products. This strategic sharing is instrumental in identifying new opportunities, reducing development risks, and preempting potential problems, thereby contributing to a firm's adaptive and innovative capabilities (Zhou & Benton, 2007; Huo et al., 2021).

Information sharing enables access to external knowledge and technology, crucial for successful new product development. It fosters inter-firm collaboration, trust, and efficiency in product development processes (Ragatz et al., 2002; Swink & Song, 2007; Bstieler, 2006).

Several factors can influence the effectiveness of information sharing in product innovation. These include the technology used for information sharing, the level of trust and commitment among stakeholders, and the level of uncertainty in the information shared (Le et al., 2021). Additionally, factors such as culture (Maras, 2017), organizational structure (Cherian, 2007), and leadership (Hoch, 2014) can also play a role in determining the effectiveness of information sharing.

2.3. Product innovation capability

PIC has been defined and operationalized in various ways in the literature. Some researchers define PIC as developing and introducing new products (Markovic & Bagherzadeh, 2018). Others describe it as improving existing outcomes or continuously creating new product lines. Still, others define it as the ability to manage the entire product development process efficiently and effectively, from idea generation to commercialization. Despite these different definitions, there is a common understanding that PIC is an intricate and multi-faceted concept incorporating technical and organizational abilities. As a result, Product Improvement Capability (PIC) describes a business's propensity to create and launch innovative new products (Najafi-Tavani et al., 2018). In today's fiercely competitive marketplace, it is essential to a company's long-term survival and competitiveness (Slater et al., 2014).

The product development process, which can shed light on PIC's fundamental aspects, is the steps a business takes to create and launch a new product. These activities include idea generation, concept development, design and development, testing and validation, and commercialization. A company's PIC can be evaluated based on its ability to effectively manage and coordinate these activities (Gonzalez-Zapatero et al., 2016). Another way to understand PIC's key components or dimensions is to examine the company's resources. Resources include tangible and intangible assets, such as financial resources, human resources, technology, and knowledge. A company's PIC can be evaluated based on its ability to access and effectively utilize these resources (AL-Khatib, 2022; Najafi Tavani et al., 2013; Thomas, 2013).

In addition to the product development process and resources, the culture and leadership of a company also play a critical role in its PIC. A culture that encourages and supports innovation and leadership that is committed to innovation and provides direction and support can enable a company to create and implement new products (Szczepańska-Woszczyna, 2015).

2.4. Development of hypotheses

BDA and information sharing have profoundly impacted product innovation in recent years. By allowing companies to gather and analyze vast amounts of data, BDA has given firms the ability to gain insights into customer behavior and preferences that were previously unattainable. BDA helps in the development process of new and improved products that are better tailored to meet the needs of consumers.

BDA transforms organizational information sharing by facilitating the collection, processing, and analysis of extensive data, leading to deeper insights and more strategic decisions, thereby enhancing collaboration (Capurro et al., 2021). It uncovers hidden patterns and trends, enabling firms to disseminate more pertinent information and collaborate more effectively, ensuring that all relevant parties have access to shared data and insights for optimal decision-making (Liedong et al., 2020; Liu & Wang, 2018).

BDA also allows for more effective decision-making by providing real-time insights. With real-time data, companies can make decisions in real-time information, which leads to more accurate information and, thus, better decisions (Wan & Liu, 2021). BDA also leads to developing new technologies and platforms that facilitate information sharing. With the help of BDA, new technologies have been developed, such as data-sharing platforms and data visualization tools. These technologies make sharing information and insights easier, leading to better collaboration and decision-making (Hader et al., 2022).

Overall, BDA has had a significant impact on the way that information is shared and on the quality of it (Bahrami & Shokouhyar, 2021) and is used within organizations. By allowing companies to gather, process, and analyze vast amounts of data, BDA has enabled firms to gain insights and make more informed decisions.

Therefore, the following hypothesis has been developed:

H1: BDA has a positive effect on information sharing.

One of the vital benefits of BDA in product innovation is that it allows companies to identify trends and patterns in consumer behavior that were previously hidden. For example, by analyzing data on customer purchases and browsing habits, a company may identify patterns in the types of products that customers are most interested in (C. Lin et al., 2022). BDA can inform the development of new products or the improvement of existing ones. Additionally, BDA enables companies to segment their customers based on demographics, purchase history, and other data points, leading to more personalized products and services (Capurro et al., 2021).

BDA aids in product innovation by allowing for the swift and efficient testing of new concepts, using consumer behavior data to gauge potential success and guiding resource allocation. It also enables ongoing product performance monitoring, facilitating early detection and resolution of issues, thereby enhancing product success and reducing the risk of failure (Zhan et al., 2017).

BDA also allows companies to understand the competitive landscape more deeply. A company can identify areas where it may gain an advantage by analyzing data on the products and services offered by competitors (Calic & Ghasemaghaei, 2021). This can help a company develop products better suited to consumers' needs while positioning them more competitive in the marketplace. Additionally, BDA can enable companies to identify new market opportunities, leading to new product development and entry into new markets (Tunc-Abubakar et al., 2023).

Furthermore, BDA can enable companies to optimize their supply chain, leading to more efficient and cost-effective product development and delivery. For example, by analyzing data on inventory levels, delivery times, and other factors, companies can identify bottlenecks and inefficiencies in their supply chain, which can then be addressed to improve performance (AL-Khatib, 2022).

There are studies (Bahrami & Shokouhyar, 2021; Contreras Pinochet et al., 2021; Fernando et al., 2018; C. Lin et al., 2022; Mikalef et al., 2020; Munir et al., 2023) in the literature have found that BDA has an impact on product innovation and development.

Therefore, the following hypothesis has been developed:

H2: BDA has a positive effect on PIC.

One fundamental way that information sharing can impact product innovation is through the development of new technologies (Makkonen et al., 2014). When companies and organizations share information about their research and development activities, they can learn from one another and build upon each other's work (Ali, 2023). This can lead to the rapid advancement of technologies and the creation of new products and services that incorporate these technologies. In manufacturing, information sharing can lead to the development of new and more efficient production methods, ultimately leading to lower costs and more affordable products for consumers.

Moreover, information sharing can help companies and organizations identify new market opportunities and develop new business models. When companies share information about their customers, they can learn about their needs, preferences, and trends in their respective industries (M. J. Lin & Chen, 2008). This can help them to identify new products and services that are in high demand, as well as to develop new business models that better meet these needs. Companies can share information about consumer behavior and preferences, which can help them identify new products in high demand and develop new business models that better meet these needs (R. Lin et al., 2012).

Information sharing significantly influences product innovation by fostering collaboration and the exchange of resources among companies, which is essential for developing new technologies and services that benefit society and spur business growth (Akroush & Awwad, 2018; Fayyaz et al., 2021; Keszey, 2018; Markovic & Bagherzadeh, 2018). BDA strengthens this impact by enhancing the effectiveness and efficiency of the information-sharing process, thereby boosting the capacity for product innovation.

Therefore, the following hypotheses have been developed:

H3: Information sharing has a positive effect on PIC.

H4: Information sharing has a mediation effect on the impact of BDA on PIC.

The model of the study is shown in Figure 1.

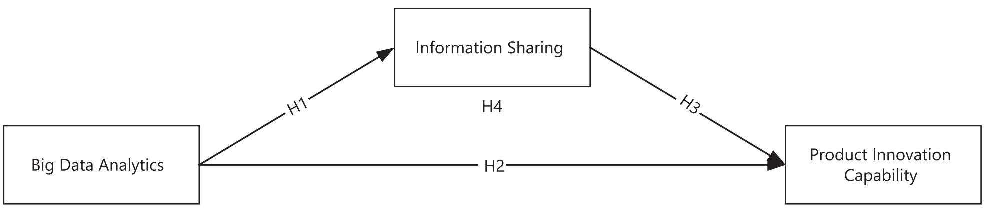

Figure 1. Research model

3. Materials and methods

3.1. Sample and data collection

A survey was emailed to 1000 manufacturing companies to investigate how BDA affects the capacity for product innovation and how information sharing mediates this effect. During January and May of 2022, the survey was available. After the initial emails were sent to the participants, 93 usable responses were collected. Only 29 valid responses were received after a second email was sent four weeks later to companies that had yet to respond to the first. A total of 122 observations were thus utilized in the analysis.

3.2. Questionnaire

There were two sections to the questionnaire used for this research. We asked eight demographic questions about businesses and respondents in the first section. Twenty-one follow-up questions were used to quantify the theoretical framework. The second section of questions used a 5-point Likert scale to gauge how respondents agreed or disagreed with each statement (1 – strongly conflict, 5 – strongly agree).

The questionnaire was adapted from the following studies to assess the variables:

1. Big Data Analytics (BDA); Wamba et al. (2020); based on ten items.
2. Product Innovation Capability (PIC); Liao and Li (2019) based on five things.
3. Information Sharing (IS); Saleem et al. (2021) based on six items.

3.3. Data analysis

There were three distinct levels of analysis in this study.

To assess the scales' validity and reliability, we conducted exploratory and confirmatory factor analyses. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test were used to ensure the appropriateness of factor analysis, with KMO values above 0.7 indicating suitability for the analysis (Field, 2017). Confirmatory factor analysis (CFA) was then used to test the distribution of variables across organizational settings. Construct validity and reliability were confirmed by good fit indices and the calculation of factor reliability and average variance extracted (AVE), with values above 0.7 for reliability and 0.4 for AVE indicating a reliable structure (Fornell & Larcker, 1981; Hair et al., 2016). Normality was checked through skewness and kurtosis values.

In Stage 2, we applied a structural equation model (SEM) to evaluate our hypotheses (H1, H2, and H3). SEM is favored for its robustness in handling complex models and its capacity to adjust for measurement error, making it prevalent in diverse research areas. It employs various statistical tests to validate constructs, including tests for convergent, discriminant, and internal consistency (Fornell & Larcker, 1981). Fit indices like the chi-squared test assess the model's data fit, and regression coefficients were analyzed to determine the support for our hypotheses.

Hayes' (2017) process macro method, which utilizes bootstrapping, was employed to test the mediation effect, where mediators are intervening factors that alter the relationship between independent and dependent variables (Baron & Kenny, 1986). Mediation is considered when both independent and dependent variables show a significant effect. However, a third variable may influence their relationship (Bennett, 2000). The process begins by establishing a link between the independent variable (X) and the dependent variable (Y), and mediation analysis can proceed even if X and Y are not directly related, as argued by some researchers (MacKinnon et al., 2000). To confirm a mediator's role, the indirect effect's significance is determined using Hayes's method, which is deemed robust due to its bootstrapping technique (Fritz & MacKinnon, 2007).

4. Findings

Some demographic characteristics of the participants are given in Table 1.

Table 1. Demographic characteristics of the firms

Sector	Frequency	Percent
Packaging / Glass	6	4.9
Paint / Chemistry	6	4.9
Iron, Steel Copper	3	2.5
Electric, Electronics, Computer	15	12.3
Energy	7	5.7
Food	19	15.6
Construction / Building Materials	10	8.2
Machine	4	3.3
Furniture / Forest Products	4	3.3

End of Table 1

Sector	Frequency	Percent
Automotive	6	4.9
Plastic	3	2.5
Health, Medicine, Hygiene, Cosmetics	19	15.6
Textile, Shoes	20	16.4
Total	122	100.0
Years of operation	Frequency	Percent
0–10	31	25.4
11–20	20	16.4
21–30	29	23.8
31 and above	42	34.4
Total	122	100.0
Number of employees	Frequency	Percent
0–50	30	24.6
51–150	8	6.6
151–250	9	7.4
251 and above	75	61.5
Total	122	100.0
Responding department	Frequency	Percent
Production	11	9.0
Purchasing	9	7.4
Marketing / Sales	38	31.1
Management	28	23.0
Other	36	29.5
Total	122	100.0

Before pilot testing, construct validity and reliability of the research model were evaluated using KMO, factor analyses, and reliability tests, with KMO values above 0.70 indicating sufficient sample size for reliable conclusions. Results are presented in Table 2.

The EFA results indicated factor loadings above 0.50 and a KMO value over 0.70, with significant Bartlett's test results allowing for factor analysis. The scales accounted for over half the variance, with skewness and kurtosis values within the normal range.

Table 2. Exploratory factor analysis results

Items	Factor Loadings	Skewness	Kurtosis	Mean	Std. Deviation
BDA					
BDA1	0.862	–0.897	0.923	3.78	0.949
BDA2	0.857	–0.864	0.794	3.71	0.975
BDA3	0.822	–0.814	0.631	3.78	0.940
BDA4	0.865	–1.009	1.233	3.93	0.955

End of Table 2

Items	Factor Loadings	Skewness	Kurtosis	Mean	Std. Deviation
BDA5	0.856	–1.048	1.087	4.04	0.922
BDA6	0.899	–0.990	1.156	3.85	0.951
BDA7	0.887	–1.137	1.473	3.98	0.931
BDA8	0.810	–1.318	2.331	4.16	0.894
BDA9	0.858	–1.362	2.872	4.04	0.857
BDA10	0.842	–1.048	1.480	3.95	0.908
KMO: 0.948 Approx. Chi-Square: 1140.897df:45 sig.:0.000 Total Variance Explained: % 73.316					
PIC					
PIC1	0.898	–1.131	1.321	3.68	0.981
PIC2	0.920	–1.265	1.724	3.89	1.014
PIC3	0.908	–0.935	0.668	3.67	1.056
PIC4	0.867	–0.863	0.623	3.73	0.971
PIC5	0.852	–0.650	0.537	3.68	0.912
KMO: 0.871 Approx. Chi-Square: 512.491df:10 sig.:0.000 Total Variance Explained: % 79.115					
Information Sharing					
IS1	0.903	–0.980	1.387	3.80	0.915
IS2	0.831	–0.660	0.361	3.56	0.971
IS3	0.911	–0.890	0.918	3.74	0.969
IS4	0.906	–0.743	1.595	3.72	0.816
IS5	0.921	–1.001	2.407	3.86	0.764
IS6	0.930	–0.837	1.443	3.87	0.823
KMO: 0.927 Approx. Chi-Square: 730.963 df:15 sig.:0.000 Total Variance Explained: % 81.165					

Scales were subjected to EFA and then Confirmatory Factor Analysis (CFA). Table 3 displays the goodness-of-fit results from the CFA.

Table 3. CFA goodness-of-fit values

Variable	χ^2	df	χ^2/df	GFI	CFI	NFI	SRMR	RMSEA
Criterion			≤5	≥.85	≥.90	≥.90	≤.08	≤.08
BDA	56.443	34	1.66	0.918	0.98	0.952	0.0285	0.074
PIC	20.47	5	4.094	0.937	0.97	0.961	0.0317	0.16
IS	12.767	9	1.419	0.967	0.995	0.983	0.0161	0.059

The CFA results show that the scales have sufficient goodness of fit.

The reliability analysis of the scales followed the exploratory and confirmatory factor analyses. Table 4 displays the outcomes of the reliability analysis, such as the alpha coefficient, the Average Variance Extracted (AVE), and the Composite Reliability (CR) values computed for component validity.

Results from a reliability analysis show that the scales can be trusted, with alpha values greater than 0.70. Both the AVE and CR are greater than 0.50, and both are greater than 0.70. Based on these results, it seems that the scales are valid and reliable. In addition, Table 5 displays the results of a correlation analysis performed before the research model was put to the test.

Table 4. Reliability and validity

Variable	AVE	CR	Cronbach' Alpha
BDA	0.699	0.958	0.959
PIC	0.736	0.933	0.934
IS	0.773	0.953	0.950

Table 5. Correlations between variables

	Mean	Std. Deviation	BDA	PIC	IS
BDA	3.9221	0.79466	1		
PIC	3.7295	0.87836	0.599**	1	
IS	3.7582	0.78762	0.589**	0.553**	1

The correlation analysis results indicate a moderate, statistically significant correlation in the same direction between the variables at the 0.01 level of significance.

A structural equation modeling analysis was conducted to verify the study's hypotheses after the validity and reliability of the scales were established. The analyzed model is depicted in Figure 2, and goodness-of-fit values are shown in Table 6. The results indicate that the model is sufficiently accurate to be accepted.

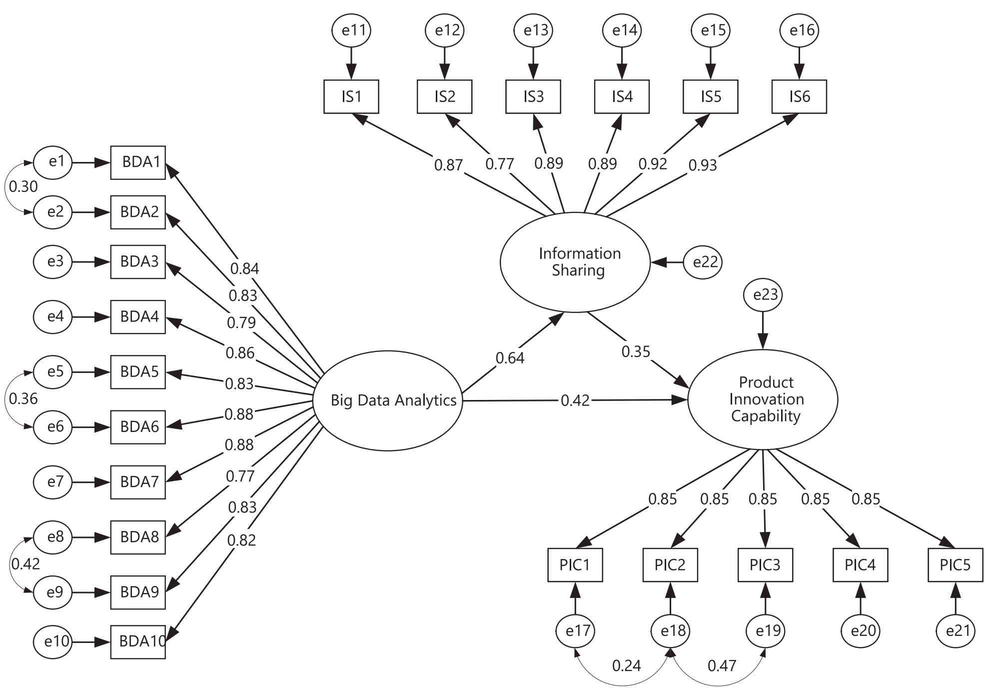

Figure 2. Structural equation model

Table 6. Model's goodness of fit values

Variable	χ^2	df	χ^2/df	GFI	CFI	NFI	RMSEA
Criterion			≤5	≥.85	≥.90	≥.90	≤.08
Model	227.278	181	1.228	0.856	0.979	0.919	0.051

The analysis results can be seen in Table 7. The structural equation modeling analysis results indicate that BDA positively and significantly affects knowledge sharing and product innovation capacity. It was also found that knowledge sharing affects product innovation capacity. As a result, Hypotheses H1, H2, and H3 are supported.

Table 7. SEM findings

			Estimate	SE.	CR.	P
IS	<---	BDA	0.642	0.089	7.182	***
PIC	<---	IS	0.355	0.098	3.454	***
PIC	<---	BDA	0.419	0.1	4.012	***

In order to test Hypothesis H4, PROCESS MACRO analysis was conducted. Figure 3 displays the data analysis results.

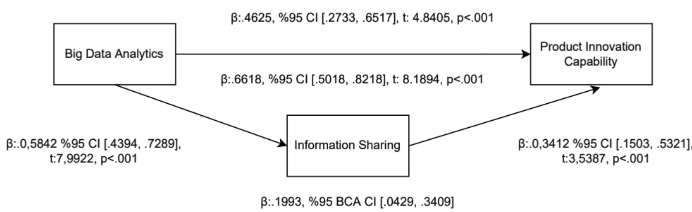

Figure 3. PROCESS MACRO results

The analysis indicated that BDA significantly enhances information sharing with a beta coefficient of 0.5842, a p-value below 0.001, and an R^2 of 0.3474, explaining 34.74% of the variance in information sharing.

The results indicate that information sharing positively influences product innovation capacity with a beta of 0.3412, and BDA's impact on innovation is significant with a beta of 0.4625. With p-values below 0.001, these relationships are statistically significant, and an R^2 of 0.4169 suggests that BDA and information sharing explain 41.69% of the variance in innovation capacity.

BDA significantly impacts product innovation capacity independently, with a beta of 0.6618 and a p-value below 0.001, confirming statistical significance and a 95% confidence interval.

The analysis revealed that BDA's indirect effects on product innovation via information sharing are significant, with a beta of 0.1993 and a high effect size of 0.1803, supporting the H4 hypothesis of a substantial mediating effect of information sharing, as indicated by a confidence interval not including zero.

5. Discussion

This study investigated the relationship between BDA, information sharing, and PIC. According to the study's analyses, BDA, information sharing, and PIC are all positively correlated. The study's results propose that BDA and information sharing significantly and positively influence PIC. Additionally, the results suggest that the influence of BDA on PIC may be mediated via information sharing as an intermediary variable.

The study's first finding demonstrated that BDA significantly and positively affects PIC. This discovery is consistent with prior investigations that have discovered how business process analytics (BDA) can enhance organizational efficiency and decision-making (Sun & Liu, 2021; Chierici et al., 2019; Intezari & Gressel, 2017; Janssen et al., 2017). Furthermore, BDA can assist firms in attaining a competitive advantage by identifying novel opportunities (Kache & Seuring, 2017) and mitigating risks associated with product development.

Furthermore, the findings demonstrated that exchanging information substantially and positively affects PIC. This is further corroborated by prior investigations that discovered enhanced collaboration and communication among diverse stakeholders can result from effective information sharing; such research has contributed to more efficient and effective product development (Najafi-Tavani et al., 2018; Perks, 2000; Vázquez-Casielles et al., 2013). Moreover, the research findings suggest that exchanging information substantially favors PIC via BDA. This discovery implies that the exchange of information may serve as a crucial enabler for the beneficial effects of BDA on PIC.

The findings of this study have several implications for practitioners and researchers:

- *From a theoretical perspective*, these results contribute to the expanding corpus of literature concerning the effects of BDA and information sharing on the performance of organizations. The empirical evidence presented in the study substantiates the notion that BDA can serve as a beneficial instrument for organizations seeking to enhance their innovation capabilities by positively impacting PIC. The results regarding the beneficial effects of information sharing on PIC are consistent with previous investigations that emphasize the significance of efficient collaboration and communication in the process of developing new products.
- *From a managerial perspective*, the results of this study have several implications for organizations looking to improve their product innovation capabilities. Initially, organizations seeking to enhance their innovation performance may find it advantageous to invest in BDA capabilities, according to the findings. The results underscore the significance of organizations investing in BDA capabilities to maintain competitiveness and enhance their PIC. Big data analytics (BDA) technologies and tools, including Hadoop, Spark, and NoSQL databases, should be considered by organizations to extract insights and knowledge from large and complex datasets and manage the volume, velocity, and variety of big data. Furthermore, the findings underscore the significance of sufficient information dissemination in promoting cooperation and correspondence among various parties involved, including clients, suppliers, and staff, thereby potentially enhancing the efficacy and productivity of product development. In order to foster a culture of trust and dedication and to encourage information sharing and collaboration among stakeholders, organizations should develop strategies such as establishing formal and informal communication channels. Finally, the results of this study suggest that the governance of BDA processes should be directed to valuable business development capabilities. Organizations should consider the role of BDA strategies in their informa-

tion sharing, as it may play a critical role in realizing the total value of BDA for product innovation. This highlights the importance of aligning BDA processes with business goals and managing resources effectively to ensure that insights generated from data are used to support and improve PIC.

6. Conclusions

This study investigated the impact of Big Data Analytics (BDA) and information sharing on Product Innovation Capacity (PIC). The analysis revealed that BDA and information sharing positively and significantly impact PIC. The study also found that information sharing mediates the relationship between BDA and PIC, serving as a pivotal bridge that channels insights flow from analytics to innovative applications.

The research advances theory by demonstrating the beneficial effects of BDA and information sharing on PIC in practice. The findings provide practitioners with insights into investing in BDA and fostering a culture of information sharing to enhance PIC. In particular, the transformative role of information sharing is underscored as it facilitates the utilization of BDA-derived insights for product development processes.

From a managerial perspective, the results suggest that organizations should invest in BDA and actively promote knowledge-sharing practices. This dual focus can catalyze the conversion of complex data into actionable intelligence, thereby accelerating the innovation cycle. The interplay between BDA, information sharing, and PIC highlights the necessity for a collaborative environment where information is freely circulated both internally and externally, enhancing the collective innovation potential.

However, this study is not without limitations. The sample of firms from a specific country may limit the generalizability of the results to other contexts. Additionally, the cross-sectional nature of the data constrains the ability to establish causality.

Future research could build upon this foundation by incorporating a more diverse sample of firms and employing longitudinal data to ascertain causality better. Further investigation into the roles of organizational culture and leadership in moderating the relationship between BDA, information sharing, and PIC could also yield valuable insights.

In conclusion, the interconnectedness of BDA, information sharing, and PIC is evident, with information sharing emerging as a critical facilitator. By embracing a knowledge-sharing ethos and integrating BDA into their strategic framework, organizations can enhance their innovation capabilities and, ultimately, their competitive edge in the marketplace.

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Author contributions

B.Y., S.C., I.M.-K. and R.C. were responsible for the study conception and design. B.Y and S.C. were responsible for data collection. B.Y., S.C., I.M.-K. and R.C. were responsible for data analysis and interpretation. B.Y., S.C., I.M.-K. and R.C. discussed the results and contributed to the final manuscript.

Disclosure statement

The authors have no competing financial, professional, or personal interests from other parties that are related to the subject of this paper.

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