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Revealing the Effect of Big Data Capabilities on Efficiency-Based Business Model Innovation

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Abstract

Objectives: Business model innovation is significant for corporation performance. Unclear or poorly designed business models can only achieve moderate or insignificant results in terms of performance. Under the view of innovation theory, multiple factors affect the efficiency-based business model innovation. Big data capabilities, knowledge creation, and Institutional environment are proposed. *Methods:* With the collection from 513 pig farming enterprises in China, this research analyzes the relationships among big data capabilities, knowledge creation, institutional environment, and efficiency-based business model innovation by SMART-PLS. *Findings:* As a result, big data capabilities have a positive impact on efficiency-based business model innovation. Big data capabilities have a positive impact on knowledge creation. Knowledge creation has a positive impact on efficient business model innovation, which is supported. Knowledge creation mediates between big data capabilities and efficient business model innovation, which is supported. The impact of institutional environment regulation knowledge creation on efficient business model innovation. *Novelty:* This research has theoretical and practical contributions. This study implies the theory of innovation to the practice. And it also enriches the literature and research on business model innovation.

Keywords:

Big Data Capabilities;

Knowledge Creation;

Institutional Environment;

Efficiency-Based Business Model Innovation.

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1- Introduction

Business model innovation refers to the creation of new business models that aim to create total value for all stakeholders. It lays the foundation for the acquisition of core enterprise values by defining the overall value chain or creating total value in transactions, which can be seen as the upper limit of a company's value capture potential [1].

Knowledge information drives business model innovation. Knowledge is not an exogenous economic growth variable but an intrinsic core factor. The difference in knowledge creation ability will lead to huge differences in enterprise innovation performance. There are two ways for enterprises to create knowledge: one is to integrate externally acquired knowledge with existing enterprise knowledge [2]; the other is to recombine internal organizational knowledge, such as new product development [3]. Obviously, in the face of dynamic changes in the external environment, relying solely on internal resources for knowledge creation is no longer enough to meet the enterprise's demand for new knowledge [4]. Integrating external knowledge with existing platform enterprise knowledge can achieve all-round knowledge innovation. Enterprises need to search for internal and external information to solve problems in their operations. The organization's search process is the process of discovering new opportunities and solving problems. In the context of open innovation, it is difficult for organizational resources to meet the demands of innovation. Enterprises should

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actively search for external new knowledge to obtain new ideas and concepts to solve innovation problems and avoid falling into the "innovator's dilemma" [5]. Overall, information and knowledge searches are bringing changes to business model innovation and enterprise efficiency.

Big data drives business model innovation and affects enterprise efficiency. The rapid development of information technology and the Internet has brought an all-round impact to traditional production and operation modes in the industrial economy era. Data and information integration have formed the operating form and structure of the network economy, integrating various types of things such as equipment, people, and enterprises. Under the background of big data, enterprises use big data technology and management tools to integrate information resources, complete the transformation from data to knowledge, and accelerate knowledge creation [6]. For enterprises, upgrading big data to a capability level can fully leverage the long-tail effect of the Internet by analyzing massive amounts of data, creating more value for customers and partners [7]. Big data capabilities are key factors that support enterprises' continuous dynamic matching with the digital environment and drive their business model innovation. It is also crucial for enterprises' survival and development. Overall, big data capabilities promote changes in enterprise business models.

To sum up, with the challenges from knowledge information, big data, and the institutional environment, how to innovate the enterprise business models to improve the enterprise efficiency is very important. Therefore, the relationships among knowledge information, big data, institutional environment, business model innovation, and enterprise efficiency should be tested, for better understanding, leading to better strategic management for the enterprises. Although there are several studies on this issue, it was found that the research results were inconsistent. Moreover, the types of businesses selected for research data are different. Therefore, to fill the gaps, this research has set the objective to test the relationship among the variables by using data from agricultural businesses. This is different from previous research. It is expected that the research results can help to find an appropriate model for determining efficient business strategies for entrepreneurs, especially in the agricultural sector.

2- Theoretical Background and Hypotheses Development

Innovation is a complex system, whether at the technical level or on a larger societal scale [8]. The integration theory of innovation is another innovation theory after Schumpeter's (1982) [9] innovation theory, national innovation system theory, and regional innovation system theory.

With the development do innovation theory, some scholars compare business model innovation with technological innovation or service innovation and believe that the former does not necessarily discover new products or services but uses new methods to create and deliver existing products or services and gain value from them [10]. Some scholars think that business model innovation is a new type of innovation that originates from new ideas and emphasizes it as an iterative process. From this perspective, business model innovation is not about looking back because experience cannot determine the feasibility of future business models [11]. Business model innovation is not about competing with competitors because it is not about copying but creating new mechanisms to gain value and revenue. Business model innovation is not simply technological innovation or product innovation. Its essence is the change in the form or implementation of business model functional elements the search for new commodity value space or changing the value chain process of the enterprise or optimizing the influence path of the enterprise, etc.

Given the lack of literature analyzing the impact of big data analysis capabilities on business model innovation [12], this study used some existing empirical studies to construct hypotheses. First, Mikalef et al. (2019) [13] found that enterprise big data capabilities not only have a positive impact on companies' ability to develop incremental innovations (by making subtle changes to existing products, services, and processes) but also have a positive impact on disruptive innovations (by creating new products and services). Similarly, evidence from the beneficial role of IT infrastructure in promoting knowledge exploration and utilization for innovative purposes [14].

Jimenez et al. (2019) [15] have demonstrated the positive impact of IT capabilities (including data collection and analysis capabilities). Finally, Ransbotham & Kiron (2017) [16] used a survey-based study of practitioners and scholars to emphasize the importance of having sufficient data governance skills in order to effectively innovate processes, products, services, and entire business configurations. Lu et al. (2022) [17] further expect that external knowledge search will mediate the relationship between executive team identification ability and efficiency-based business model innovation among large enterprises with high levels of big data management skills. Specifically, in the case of high levels of big data management skills, the relationship between executive team identification ability and external knowledge search will be stronger, and enterprises will be more proactive in conducting extensive and deep external knowledge searches to fill gaps in their knowledge, reduce or even eliminate gaps between enterprises and knowledge sources, enrich their knowledge base, and thus enhance their ability to innovate efficiency-based business models and promote their willingness to innovate efficiency-based business models [18].

On the contrary, lower levels of big data management skills will reduce the ability of the executive team to identify market potential opportunities or threats, thereby weakening the driving force behind external knowledge search, and leading to less efficiency-based business model innovation activities. Lu et al. (2022) [19] believe that big data management skills will mediate the mediation effect between external knowledge search and the identification ability and efficiency-based business model innovation of the executive team. The higher the level of big data management skills, the stronger this mediation effect will be, and vice versa. Overall, this research proposes the hypothesis;

H1: Big data capabilities have a positive impact on efficiency-based business model innovation.

Big data refers to large volumes of various types of data (McAfee et al. 2012) [20] that are scattered across different organizational information systems and are not structurally linked. Similarly, big data also constitutes the source of digital real-time data streams.

According to the detailed discussion of dynamic capability theory on big data practice, Zhao (2021) [21] defines big data capability as the ability of an enterprise to identify various sources of large-volume data flowing rapidly and collect, store, and analyze these big data to achieve its strategic and operational goals. Because it is a special kind of knowledge generation capability, big data practice has generated knowledge about self-transformation. This related dynamic capability of big data has four basic features that can be represented by a complete resource package: skillset, capabilities, and cultural values. These four basic features include data sets, toolset, skillset, and mindset [22]. In addition to data, another major resource type used in big data capabilities is a combination of hardware, software, and complex IT infrastructure that can collect, store, transform, and analyze big data. This constitutes the toolset. Furthermore, big data capabilities require the acquisition of data analysis skills, which are organizational knowledge-shaping capabilities [6]. This is the skill set. Although this is not an exclusive list, the characteristics of big data are sufficient to demonstrate that big data capabilities are not a single technology but rather a multifaceted interactive element package. Li et al. (2021) [23] believes that big data capabilities are related to the ability to use information related to markets, customers, and consumers, which enables companies to measure external trends and changes

Knowledge creation is described in the literature of expertise and innovation as how companies, organizations, and academic fields develop and maintain ideas necessary for innovation [24]. Knowledge creation depends on the conditions under which creative work of ideas is valued and there are mechanisms to select the most promising ideas for further development and reward creativity [25].

Platform companies with strong big data capabilities are often better at utilizing big data technology for data collection and data scraping to improve their ability to search for diverse knowledge from partners, customers, competitors, etc., and quickly screen and integrate external knowledge to avoid resource consumption and waste. Overall, this research proposes the hypothesis;

H2: Big data capabilities have a positive impact on knowledge creation.

Innovation is the process by which companies can deploy and utilize their knowledge to create or improve products and technologies [26]. It enables the potential value of enterprise knowledge to be realized and further promotes the survival and competitive advantage of enterprises [27]. Existing research has explained the role of innovation in corporate success.

Business models are described as structural templates that describe the transactions between focus companies and external organizations in the production factor market and product factor market [28]. They go beyond the boundaries of the focus company and are composed of a series of interdependent activity systems [29]. When designing this activity system, companies need to consider two aspects: design elements and design themes. Design elements describe the architecture of the business model, including value propositions, partnerships, cost structures, revenue models, etc. [30]. Design themes describe the overall format of the enterprise business model, which helps with conceptualizing the business model [31]. Design themes focused on efficiency and innovation have been frequently mentioned in existing literature [32]. Design themes focused on efficiency emphasize transaction efficiency and the business model's involvement in transaction costs; design themes focused on novelty concentrate on introducing new transaction methods or establishing connections with new transaction partners. Although these efficiency-oriented business models are essentially optimizing the "cost-value" structure by open value creation chains and promoting information exchange among multiple participants through systematic cost reduction.

Efficiency-oriented business model innovation refers to the innovative way in which different parties engage in transactions, with the goal of systematically improving transaction efficiency without changing the value logic of industry products or services. As a result, it places greater emphasis on using logic and represents an optimization and upgrading of the mainstream business models within the industry. In today's dynamic business environment, business models are considered an important tool for enterprises to improve performance and gain competitive advantages [33]. For example, Veblen et al. (1997) [34] pointed out that effective business models can help companies gain new customers first, thus giving them a leading advantage. Lestari et al. (2020) [35] found that not only can corporate strategies bring about competitive advantages, but business model design can also bring about competitive advantages. Latifi et al. (2021) [36] found that design themes focused on efficiency and innovation have significant effects on enterprise performance. Li et al. (2022) [37] found that the fit between business models and competitive strategies has a significant positive impact on enterprise profitability

Knowledge creation can enhance enterprises' interaction with external environments, improve their learning ability, and strengthen their ability to perceive and capture opportunities in the external environment through processing and institutionalizing external knowledge acquired. This, in turn, promotes enterprise business model innovation. External knowledge often has heterogeneous characteristics and is difficult to directly use in the process of business model innovation. Only by deconstructing external knowledge, effectively integrating internal and external knowledge through continuous experimentation, creating new knowledge, and applying it to areas such as enterprise value proposition innovation, business process reengineering, new product and service development, and marketing channel redesign, can platform companies overcome the bottleneck of business model innovation, change the original inertia of the platform, and increase the success rate of business model innovation [38]. Overall, this research proposes the hypothesis;

H3: Knowledge creation has a positive impact on efficient business model innovation.

Based on the aforementioned analysis, platform companies can utilize big data capabilities and their interaction to acquire external market knowledge. However, in a complex external environment, influenced by differences in enterprise-existing knowledge bases, external knowledge may not be fully matched by the enterprise, making it difficult for the platform to directly absorb, disseminate, and utilize external knowledge. Some specific knowledge elements may not play their value in the intended way or even conflict with the enterprise's existing knowledge. In addition, while external knowledge can help platform companies quickly develop new products and services, optimize business processes, and innovate profit models, without complementary knowledge creation efforts, it will be difficult to form a competitive advantage over incumbent businesses [39]. Overall, this research proposes the hypothesis;

H4: Knowledge creation mediates between big data capabilities and efficient business model innovation.

Numerous scholars have studied the moderating effects of different factors in the institutional environment on business model and performance. Bank dividend policies have a positive impact on bank profitability, while higher institutional environments or stricter bank regulations can reduce bank profitability [40]. In the relationship between institutional environment and bank performance, Hartwell et al. (2015) [41] found a positive correlation and believed that dividend policies have a positive impact on bank profitability. He & Ortiz (2021) [42] used design thinking and wireless technology analysis of big data to improve the agility of business model innovation. Highly efficient business model design places great emphasis on the full sharing of information, injecting vitality into technological innovation and new product development for enterprises [43]. This helps enterprises implement novel business model designs and improve their innovation performance [38]. Sun et al. (2020) [25] through extensive research has shown that business model innovation is an important lever for improving the sustainable development performance of enterprises, which our study not only refinements the business model innovation theory from the enterprise level to the enterprise level but also provides theoretical guidance for manufacturing companies to enhance equipment maintenance service innovation and service performance from the value source to form differentiated and sustainable competitive advantages. Overall, this research proposes the hypothesis;

H5: The impact of institutional environment regulation knowledge creation on efficient business model innovation.

Figure 1, shows the flowchart of the research methodology through which the objectives of this study were achieved.

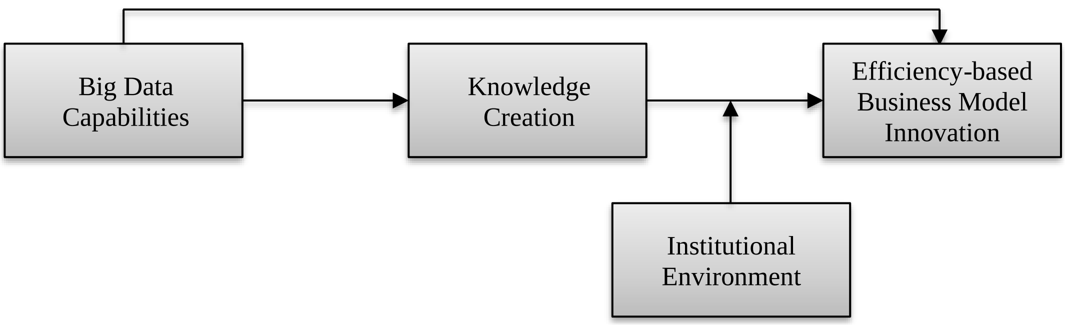

Figure 1. Conceptual research of this research

3- Material and Methods

3-1- Sample and Procedure

Based on data from Qichao.com (*www.qcc.com*) and the China State Administration of Market Regulation (*www.samr.gov.cn*), it can be observed that the number of pig farming enterprises in China is dynamically adjusted every year. In 2018, 33,800 new pig farming-related enterprises were added, a decrease of 36.65% compared to the previous year. In 2019, 31,500 new enterprises were added, a decrease of 6.97%. In 2020, 52,800 new enterprises were added, a growth of 67.76%. In 2021, 24,600 new enterprises were added, a decrease of 53.41%. In 2022, 16,300 new enterprises were added, a decrease of 33.54%. Although the number of newly added enterprises has decreased year by year, the total number of pig farming enterprises in China is gradually stabilizing. As of the end of 2022, there were 359,500 pig farming-related enterprises in China, which are the main research subjects of this study.

The present research conducted an online survey with 513 participants to investigate 513 pig farming enterprises. The data analysis examined the relationships between different variables, including gender, educational background, work tenure, position, age, nature of company, retention time, and industry, based on the feedback from the respondents. For instance, in this dataset, females slightly outnumbered males, and the most common education background was a master's degree, with most respondents holding positions as chairpersons or general managers. Additionally, private enterprises were the most common type of company, and equipment manufacturing was the most prevalent industry.

Specifically, Table 1 presents descriptive statistics, including categories, frequencies, and percentages of different variables. Gender consisted of two categories, with 236 males accounting for 46% of the total population and 277 females accounting for 54%. Education background was divided into four categories: high school and below (26 individuals, 5.1%), undergraduate (206 individuals, 39%), master's degree (265 individuals, 51.7%), and doctorate (22 individuals, 4.3%). Work tenure was divided into four intervals: less than 1 year (90 individuals, 17.5%), 1-2 years (195 individuals, 38%), 3-4 years (154 individuals, 30%), and 5 years and above (74 individuals, 14.4%). Position included different categories, with 463 individuals serving as chairpersons or general managers (90.3%), 39 individuals as top managers (7.6%), 9 individuals as middle managers (1.8%), and 2 individuals as grassroots managers (0.4%). Age was distributed across three intervals: under 30 years of age (125 individuals, 24.4%), between 30 and 40 years old (186 individuals, 36.3%), between 40 and 50 years old (129 individuals, 25.1%), and 50 years or older (73 individuals, 14.2%). The nature of the company was categorized into four types: state-owned enterprises (106 individuals, 20.7%), foreign-funded enterprises (95 individuals, 18.5%), joint ventures (44 individuals, 8.6%), and private enterprises (268 individuals, 52.2%).

Table 1. Descriptive statistics

Variable	Categorical	Frequency	Percent (%)
Gender	Male	236	46
	Female	277	54
Education background	High school and below	26	5.1
	Undergraduate	200	39
	Master	265	51.7
	Doctor	22	4.3
Work tenure	Less than 1 year	90	17.5
	1-2 years	195	38
	3-4 years	154	30
	5 years and above	74	14.4
Position	Chairman or General manager	463	90.3
	Top managers	39	7.6
	Middle managers	9	1.8
	Grassroots managers	2	0.4
Age	Under 30 years of age	125	24.4
	Between 30 and 40 years old	186	36.3
	Between 40 and 50 years old	129	25.1
	50 years or older	73	14.2
Nature of company	State-owned enterprises	106	20.7
	Foreign-funded enterprises	95	18.5
	Joint ventures	44	8.6
	Private enterprises	268	52.2

3-2- Measures

A questionnaire instrument with a Likert scale of one to five points was utilized to assess abusive supervision, with 1 representing strongly disagree and 5 indicating strongly agree.

Efficiency-based Business Model Innovation (EBI)

The measurement of business model innovation has been a topic of ongoing research. Through case studies and data analysis, different categories of business model innovation have been identified, leading to variations in measurement methods. There is also a lack of measurement based on big data collection and analysis, although Zott & Amit (2007) [44] developed a scale for measuring enterprise model innovation through big data analysis, dividing it into efficiency-based and novelty-based models. This study adopts the scale developed by Zott & Amit (2007) [44]. Constructing the scale of business model innovation and establishing a sound mechanism can enrich the theoretical application of business model innovation.

Big Data Capabilities (BDC)

Currently, there is no consensus among academic researchers on the measurement scale of big data capabilities. Most foreign research scholars focus on the definition of IT capabilities and emphasize big data analysis capabilities [45, 46]. However, this study believes that big data capabilities refer to the ability of Internet platform companies to integrate internal and external data resources, conduct in-depth mining and analysis using big data technology, gain insights and predictions into market knowledge, and ultimately enhance the adaptability of the platform to external dynamic environments. Its composition mainly includes three aspects: big data integration capability, analysis capability, and prediction and insight capability. You (2019) [47] developed a measurement scale of big data capabilities based on the specific practice background of large enterprises in Guangdong Province, China. This scale has good validity and has been referenced by many subsequent scholars in their research.

Knowledge Creation

This study references the measurement results of scholars such as Lawson (2002) [48] to measure knowledge utilization from the perspective of enterprises using new knowledge for product and service development.

Institutional Environment

In this study, the institutional environment is a moderator variable. Under the scenario of business model innovation, we will verify whether the relationship between knowledge creation and business model innovation will be affected by the external moderating effect of the institutional environment. The institutional environment is an important feature of the external environment faced by enterprises. The subjectiveness of measuring the external environment is relatively strong, and the subjective perception and response of senior management personnel towards the environment also affect their strategic orientation [49]. Therefore, it may be more appropriate to evaluate the subjective evaluation of the institutional environment. This study uses the scale developed by Busenitz et al. (2000) [50], as the results of the reliability and validity of the institutional environment scale developed by Busenitz et al. (2000) [50] are relatively good.

3-3- Analytical Approach

The study will use the general data processing methods of Hoyle (1995)'s [51] structural equation modeling. Firstly, the validity of the questionnaire data will be verified, and the data will be standardized, removing erroneous and missing data. Secondly, descriptive analysis will be conducted on the data, mainly involving mean, maximum, minimum, standard error, and correlation analysis with SPSS vison23 [52], as well as statistical analysis of population characteristics such as gender, age, industry, position, work experience, education, etc. Thirdly, data analysis will be conducted on the collected data to be tested by SMART-PLS software analysis. Reliability and validity analysis will be conducted on the data, with reliability evaluated using Cronbach's alpha coefficient with a value of 0.7 or higher, and validity evaluated using construct validity (AVE) and discriminant validity (DV); Finally, path analysis will be conducted using the Bootstrapping method of structural equation modeling with repeated sampling of 5000 times to construct a 95% confidence interval to test the mediating role of network construction ability and network management ability and test the model's credibility with reference indicators.

4- Results

4-1- Measurement Tests

Table 2 presents the correlation matrix of the variables in this study, displaying the correlation coefficients between different variables. The correlation coefficient is a statistical measure of the strength and direction of the linear relationship between two variables, with a range of -1 to +1. It is indicated that there are correlations among big data capabilities (BDC), knowledge creation (KNC), institutional Environment (INE), efficiency-based business model innovation (EBI).

Table 2. **Mean, Std. Deviation, and Correlations of variables**

	Mean	Std. Deviation	1	2	3	4	5	6	7	9	10	11
1. Gender	0.54	0.499	1									
2. Education background	2.55	0.660	0.013	1								
3. Work tenure	2.41	0.940	-0.123**	-0.079*	1							
4. Position	1.12	0.408	-0.067	0.031	0.168**	1						
5. Age	2.29	0.990	-0.123**	0.022	0.648**	0.037	1					
6. Nature of company	2.92	1.237	0.007	0.018	0.015	-0.078*	-0.054	1				
7. BDC	3.72	0.872	0.099*	0.028	-0.052	0.040	-0.115**	-0.022	1			
9. KNC	3.56	0.993	-0.014	0.028	-0.033	0.011	-0.105**	-0.045	0.538**	1		
10. INE	3.60	0.818	0.026	0.001	-0.034	-0.038	-0.055	0.074*	0.226**	0.385**	1	
11. EBI	3.59	0.914	0.076*	0.014	-0.013	0.014	-0.071	0.034	0.516**	0.611**	0.456**	1

** Correlation is significant at the 0.01 level (1-tailed); * Correlation is significant at the 0.05 level (1-tailed).

Notes: Big data capabilities (BDC); Knowledge creation (KNC); Institutional Environment (INE); Efficiency-based business model innovation (EBI).

When analyzing the data in Table 3, several key statistical indicators need to be considered, which are commonly used to assess the reliability and validity of the measurement model. This table appears to be derived from a study that utilizes structural equation modeling (SEM) or a similar multivariate analysis method to evaluate different constructs (such as knowledge creation, efficiency-based business model innovation, etc.). The following is an analysis of the data in the table:

Table 3. **Internal consistency reliability and convergent validity**

Constructs	Indicators	Loadings	VIF	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
Knowledge creation (KNC)	M1	0.836	2.325	0.905	0.905	0.927	0.678
	M2	0.818	2.218				
	M3	0.827	2.251				
	M4	0.817	2.166				
	M5	0.827	2.225				
	M6	0.814	2.115				
Efficiency-based business model innovation (EBI)	Y1	0.770	1.874	0.901	0.903	0.922	0.628
	Y2	0.763	1.865				
	Y3	0.800	2.132				
	Y4	0.779	1.949				
	Y5	0.823	2.232				
	Y6	0.791	2.053				
	Y7	0.819	2.259				
Big data capabilities (BDC)	X1	0.831	2.440	0.909	0.910	0.927	0.612
	X2	0.780	2.002				
	X3	0.756	1.937				
	X4	0.781	1.981				
	X5	0.767	1.915				
	X6	0.790	2.106				
	X7	0.777	1.982				
	X8	0.776	2.002				
Institutional Environment (INE)	Z1	0.794	2.386	0.929	0.946	0.943	0.577
	Z2	0.032	1.014				
	Z3	0.817	2.571				
	Z4	0.786	2.260				
	Z5	0.791	2.312				
	Z6	0.793	2.303				
	Z7	0.803	2.436				
	Z8	0.796	2.364				
	Z9	0.770	2.141				
	Z10	0.788	2.316				
	Z11	0.770	2.119				
	Z12	0.784	2.225				
	Z13	0.796	2.387				

Factor loadings, which indicate the degree of correlation between each indicator (or measurement item) and its corresponding construct. In reliability and validity analysis, loadings above 0.7 are generally considered acceptable, indicating a strong association between the indicators and their respective constructs. From the table, it can be observed that all loadings are high, with most exceeding 0.7, suggesting the appropriateness of the model construction.

Variance Inflation Factor (VIF), which is used to detect the issue of multicollinearity, i.e., whether the variables in the model are highly correlated and thus affecting the stability of the model results. Generally, VIF values below 5 or 10 indicate no severe multicollinearity problems. The VIF values here are all within a reasonable range, indicating the absence of severe collinearity issues among the indicators [53].

Cronbach's alpha and Composite reliability, which are two indicators used to assess the internal consistency of constructs, i.e., whether the indicators of a construct measure the same concept in a coherent manner. Values exceeding 0.7 are generally considered indicative of good internal consistency. All values in the table exceed this threshold, demonstrating good internal consistency [54].

Average Variance Extracted (AVE), which measures the ability of construct indicators to explain the variance relative to their error terms and is usually used to evaluate the convergent validity of constructs. Values should be greater than 0.5, indicating that the indicators explain more than half of the construct's variance. In this table, all AVE values exceed 0.5, indicating good convergent validity [55].

Overall, the table demonstrates a measurement model with good reliability and validity for the variables in this study. All statistical indicators indicate a strong relationship between the selected indicators and their constructs, and the distinction between constructs is well-established, with no apparent multicollinearity issues. These results provide a solid foundation for subsequent causal relationship analysis or other multivariate analyses.

In Table 4, BDC, EBI, INE, and KNC represent different constructs or variables. When analyzing these data, it is looked for lower HTMT values, as lower values indicate better discriminant validity. Typically, HTMT values below 0.85 are considered indicative of good discriminant validity. These data suggest that there is some distinctiveness maintained between the variables, which is crucial for ensuring the effectiveness of the measurement tools used in the study. However, for a comprehensive analysis, other statistical data and background information on the measurements need to be considered.

Table 4. Discriminant Validity (HTMT Ratio of Correlations)

	BDC	EBI	INE	KNC
BDC				
EBI	0.569			
INE	0.243	0.497		
KNC	0.596	0.674	0.416	
INE × KNC	0.036	0.158	0.049	0.085

4-2- Hypotheses Test

As shown in Figure 2, big data capabilities (BDC) directly affect efficiency-based business model innovation (EBI) and knowledge creation (KNC). Knowledge creation (KNC) directly affects efficiency-based business model innovation (EBI). The institutional environment (INE) regulates the effect of knowledge creation (KNC) on efficiency-based business model innovation (EBI).

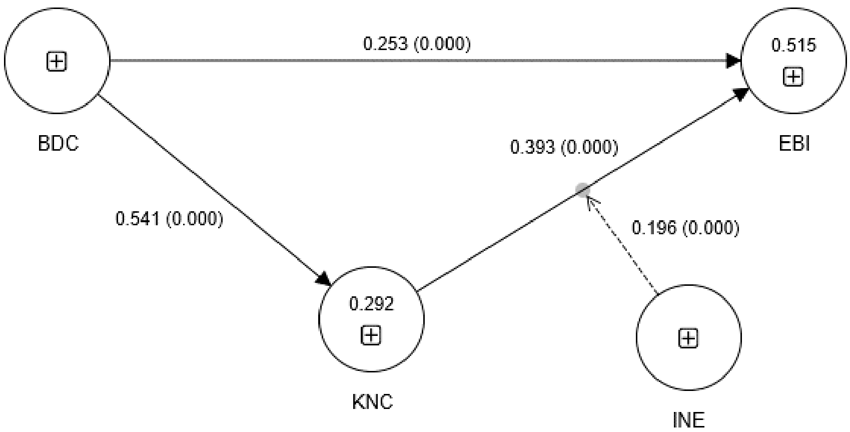

Figure 2. Results of the PLS structural path model

As indicated in Table 5, H1 refers to big data capabilities having a positive impact on efficiency-based business model innovation, which is supported (beta is 0.466, p-value is 0.000). H2 refers to big data capabilities having a positive impact on knowledge creation, which is supported (beta is 0.541, p-value is 0.000). H3 refers to Knowledge creation has a positive impact on efficient business model innovation, which is supported (beta is 0.393, p-value is 0.000). H4 refers to Knowledge creation mediating between big data capabilities and efficient business model innovation, which is supported (beta is 0.213, p-value is 0.000). H5 refers to the impact of institutional environment regulation knowledge creation on efficient business model innovation, which is supported (beta is 0.196, p-value is 0.000).

Table 5. Path coefficients

Hypotheses		Beta	SD	T-value	P values	Decision
H1	BDC → EBI	0.466	0.034	13.871	0.000	Support
H2	BDC → KNC	0.541	0.031	17.406	0.000	Support
H3	KNC → EBI	0.393	0.039	10.077	0.000	Support
H4	BDC → KNC → EBI	0.213	0.025	8.561	0.000	Support
H5	INE × KNC → EBI	0.196	0.035	5.622	0.000	Support

Notes: SD is the Standard deviation

Figure 3 depicts a simple slope analysis chart illustrating the impact of institutional environment on knowledge creation and efficiency-oriented business model innovation. The horizontal axis represents big data capability (BDC), measured by standard deviation (SD), while the vertical axis represents efficiency-oriented business model innovation (EBI). The chart includes three lines representing different conditions or groups: the red line represents INE at -1 SD (below the standard deviation), the blue line represents INE at the average level, and the green line represents INE at +1 SD (above the standard deviation). These three lines demonstrate how big data capability (BDC) affects efficiency-oriented business model innovation (EBI) under different INE value conditions. The slope (i.e., the inclination of the line) indicates the strength of the impact.

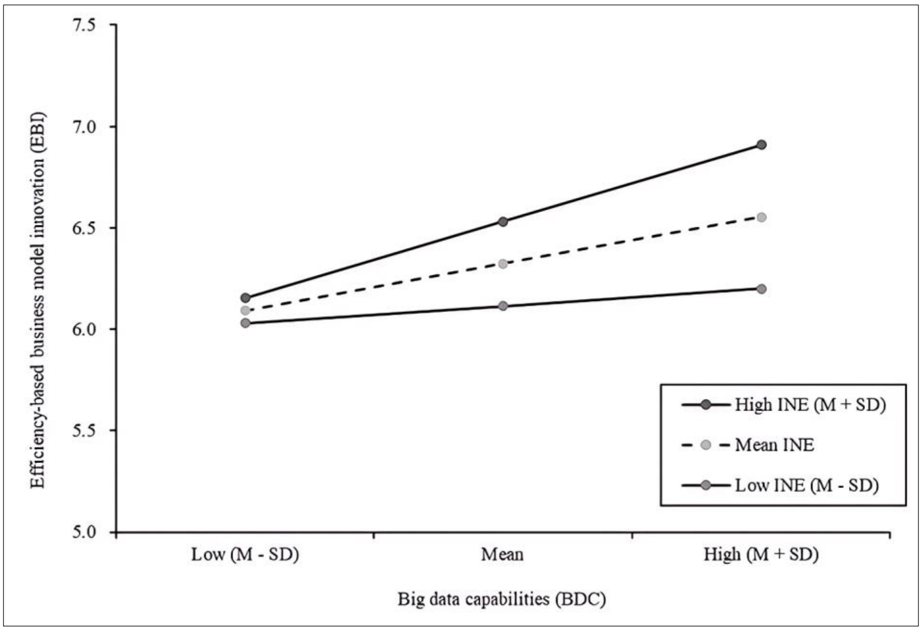

Figure 3. Simple slope analysis

From the chart, it can be observed that when the INE value is low (red line, INE below -1 standard deviation), the impact of knowledge creation on efficiency-oriented business model innovation is relatively small. When the INE value is at the average level (blue line), the impact of knowledge creation on efficiency-oriented business model innovation increases. When the INE value is high (green line, INE above +1 standard deviation), the impact of knowledge creation on efficiency-oriented business model innovation is maximized. This suggests that the INE variable may serve as a moderating variable, whereby as the INE variable increases, the positive impact of knowledge creation on efficiency-oriented business model innovation also strengthens. This analysis provides insights into the interaction effects, and understanding of the impact of knowledge creation on efficiency-oriented business model innovation under different institutional conditions.

5- Discussion, Implications, and Limitations

5-1- Discussion

Big data capabilities have a positive impact on efficient business model innovation (H1). Based on the analysis and findings of this study, it can be concluded that big data capabilities indeed have a positive impact on efficient business model innovation. The results provide empirical evidence supporting hypothesis H1. The data collected and analyzed in this study indicate a strong relationship between the level of big data capabilities within organizations and their ability to innovate their business models efficiently. Organizations that possess advanced big data capabilities are more likely to engage in successful business model innovation initiatives that enhance operational efficiency, create value, and drive competitive advantage [56].

Big data capabilities have a positive impact on knowledge creation (H2). Based on the analysis and findings of this study, it can be concluded that big data capabilities have a positive impact on knowledge creation. The results provide empirical evidence supporting hypothesis H2. Big data capabilities enable organizations to collect, process, and analyze large volumes of data from various sources. This vast amount of data provides a rich source of information that can be leveraged to gain new knowledge and understanding. By applying advanced analytics techniques, organizations can extract meaningful insights from their data, allowing them to make informed decisions, identify trends, and predict future outcomes [57].

Knowledge creation has a positive impact on efficient business model innovation (H3). Based on the research findings, it can be concluded that knowledge creation has a positive impact on efficient business model innovation, providing empirical support for hypothesis H3. The study has revealed that organizations that prioritize and invest in knowledge creation activities are more likely to achieve efficient business model innovation. Efficient business model innovation refers to the ability of organizations to develop and implement new and improved business models in a timely and effective manner.

Knowledge creation mediates between big data capabilities and efficient business model innovation (H4). Based on the research findings, it can be concluded that knowledge creation plays a mediating role between big data capabilities and efficient business model innovation. The results provide empirical support for hypothesis H4. This study has shown that organizations with strong big data capabilities are more likely to engage in knowledge creation activities. These organizations have the ability to collect, analyze, and interpret large volumes of data, which enables them to generate valuable insights and knowledge. This knowledge, in turn, becomes a critical input for driving efficient business model innovation [58].

The institutional environment regulates the impact of knowledge creation on novel business model innovation (H6). The impact of knowledge creation on novel business model innovation is profoundly influenced by the institutional environment. This research aims to provide evidence supporting the hypothesis that the institutional environment regulates the impact of knowledge creation on novel business model innovation (H6). The institutional environment plays a crucial role in shaping the innovation landscape and determining the extent to which knowledge creation can translate into the development of novel business models. Institutional factors, including formal and informal rules, regulations, and norms, create a framework within which organizations operate and innovate. One way in which the institutional environment regulates the impact of knowledge creation on novel business model innovation is through the availability of funding and support for experimentation and risk-taking. In environments with supportive institutions, organizations have access to venture capital, government grants, and other forms of financial support that enable them to explore and experiment with new business models. This financial backing reduces the risk associated with innovation and encourages organizations to invest in knowledge creation that can lead to the development of novel business models.

5-2- Theoretical Implications

The research highlights the importance of investing in big data capabilities as a strategic initiative for organizations aiming to drive efficient business model innovation. It is important to note that while big data capabilities have a positive impact on efficient business model innovation, they are not the sole determinant.

The research highlights the importance of building a data-driven culture within organizations. By fostering a culture that values data and encourages its exploration and analysis, organizations can create an environment conducive to knowledge creation. This includes promoting collaboration, providing training and resources, and establishing processes to facilitate the sharing and dissemination of knowledge generated from big data analysis.

By leveraging the insights generated through big data analysis, organizations can identify opportunities for business model optimization, explore new revenue streams, and enhance their value proposition to customers. Knowledge creation acts as a catalyst, enabling organizations to translate these insights into actionable strategies and implement them effectively.

5-3- Practical Implications

The findings suggest that big data capabilities enable organizations to gather and analyze large volumes of data, leading to valuable insights that inform the development and implementation of innovative business models. By leveraging these insights, organizations can identify new opportunities, optimize processes, and make data-driven decisions. This allows them to adapt to changing market conditions, meet customer demands, and stay ahead of their competitors

The findings suggest that organizations with strong big data capabilities are better equipped to capture, store, and analyze both structured and unstructured data. This enables them to uncover valuable insights and generate new knowledge that can be used to drive innovation, improve decision-making processes, and enhance organizational performance.

The findings suggest that knowledge creation plays a crucial role in enabling efficient business model innovation. By actively creating and acquiring new knowledge, organizations can enhance their understanding of market dynamics, customer needs, emerging technologies, and industry trends. This knowledge serves as a foundation for identifying opportunities and generating innovative ideas for business model improvements.

The findings suggest that organizations that prioritize knowledge creation as part of their strategic agenda are more likely to leverage their big data capabilities effectively. By fostering a culture of continuous learning and knowledge sharing, these organizations create an environment that encourages the generation of new ideas and the exploration of innovative business models.

The findings of the study provide strong support for the hypothesis that the institutional environment regulates the impact of knowledge creation on novel business model innovation. Organizations operating in environments with supportive funding mechanisms, collaborative networks, and adaptive regulatory frameworks are more likely to translate knowledge creation into the development of novel business models. These organizations have the necessary resources, access to knowledge networks, and flexibility to experiment with new business models and adapt to changing market conditions.

5-4- Limitations and Future Research Directions

Although this research has made theoretical contributions and managerial implications as mentioned above, it still has some limitations due to various reasons. It is necessary to further enhance its theoretical foundation and academic competence in order to gradually improve it in future academic research.

First, the majority of the sample in this study was primarily recruited through online surveys. This research method may have limitations as it only covers individuals with internet access, excluding those without internet access. Therefore, future research could consider using multiple research methods such as face-to-face interviews and telephone surveys to obtain a more comprehensive and diverse sample.

Second, there may be limitations in the selection of theoretical frameworks in this study. Different theoretical frameworks may provide different explanations and understandings of the research question. Therefore, future research could consider adopting alternative theoretical frameworks to increase the breadth and depth of the study.

Third, there may be limitations in the selection of research methods and data analysis techniques in this study. Future research could consider using more advanced and comprehensive research methods such as mixed methods research and experimental studies to enhance the reliability and validity of the research.

Fourth, there may be limitations in sample selection and sample size determination in this study. Future research could consider using more scientific and rigorous sample selection methods and increasing the sample size to improve the representativeness and generalizability of the research.

Fifth, there may be limitations in the interpretation and discussion of the results in this study. Future research could further delve into the interpretation and analysis of the research findings, and compare and contrast them with existing studies to enhance the interpretability and academic contribution of the research.

In conclusion, although this study has theoretical contributions and managerial implications, there are still some limitations. Future research can improve and enhance the study in the aforementioned areas to further enhance the quality and academic value of the research.

6- Declarations

6-1- Author Contributions

Conceptualization, B.L. and C.K.; methodology, B.L. and C.K.; formal analysis, B.L.; resources, B.L.; writing—original draft preparation, B.L. and C.K.; writing—review and editing, B.L. and C.K.; visualization, B.L.; supervision, C.K.; project administration, B.L. and C.K.; funding acquisition, B.L. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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