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The Impact of Big Data Capability on Business Model Transformation: Mediated by Knowledge Renewal and moderated by Resource Slack

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Abstract

The traditional enterprises have been significantly impacted by the digital economy and the COVID-19 pandemic, leading to a more dynamic and complex business environment. Business model innovation has become essential for enterprises to adapt effectively to this complexity. This study aims to examine the impact of big data capabilities on business model transformation. Enterprises from four regions in Jiangxi Province—Shangrao, Pingxiang, Nanchang, and Ganzhou—were selected as the research subjects, covering various industries such as technology and information technology, financial services, healthcare, manufacturing, retail, and energy. Data from 800 enterprises were collected using stratified random sampling and questionnaires, and analyzed empirically using structural equation modeling. The results demonstrate that big data capabilities significantly positively influence business model transformation, with knowledge renewal acting as a mediator between big data capabilities and business model transformation. These findings integrate the utilization of big data capabilities, knowledge renewal, and resource slack, facilitating business model transformation and enabling enterprises to achieve value growth through efficient resource sharing and management.

Keywords: *Big Data Capability, Knowledge Renewal, Business Model Transformation, Resource Slack.*

INTRODUCTION

With the rapid development and widespread application of digital technologies such as big data, cloud computing, artificial intelligence, and blockchain, the business environment of enterprises has undergone significant changes. Existing organizational boundaries are increasingly blurred, with more enterprises seeking to transcend these boundaries by changing their business models to find partners and build new value networks. For example, Pinduoduo's social e-commerce model, iQiyi's content accumulation model, and Xiaohongshu's community cross-border e-commerce model.

However, the continuous changes in the external environment, including customer preferences, market orientation, policy changes, and the dynamics of the entire ecosystem, have profound impacts on enterprises. In a highly competitive environment, some enterprises may face challenges such as resource depletion, limited capabilities, and market saturation. If enterprises cannot promptly innovate their business models based on their resource advantages, enhance their competitive edge, and meet new user demands, it will be difficult for them to create new economic growth points.

Additionally, how enterprises can accurately conduct knowledge renewal, establish effective cycles of knowledge acquisition, filtering, integration, and application, and promote the socialization and systematization of knowledge renewal are core issues that urgently need addressing in the big data era. Therefore, under the support of big data capabilities, how enterprises can utilize their abundant resources to update their business models through knowledge renewal has become an important topic of concern in current practice.

This study aims to address the following questions: First, what is the impact of big data capabilities on knowledge renewal? Second, how do big data capabilities influence business model innovation? Third, what is the impact of knowledge renewal on business model innovation? Fourth, how does knowledge renewal mediate the relationship between big data capabilities and business model innovation? Finally, does resource slack moderate the relationship between knowledge renewal and business model innovation, and between big data

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capabilities and business model innovation?

Research Contributions:First, unlike previous studies that predominantly used qualitative methods, this study employs quantitative research methods to systematically examine the relationship between big data capabilities and business model innovation, enhancing the reliability and credibility of the conclusions. Second, this study verifies the crucial role of big data capabilities in supporting business model innovation, particularly through the influence of knowledge renewal. Finally, this study integrates the knowledge spiral theory and core competency theory to construct a new theoretical framework that explains the mechanism by which big data capabilities affect business model innovation. This theoretical framework helps enterprises gain a deeper understanding of the role of big data capabilities, thereby effectively tapping market potential, enhancing competitiveness, and improving performance. Additionally, this framework guides enterprises to address emerging issues such as resource slack, reallocate resources not owned by the enterprise through big data capabilities, reevaluate the attributes and value of resources, alter traditional views on resources, and promote business model innovation to enhance competitive advantage.

Knowledge Spiral and Core Competence Theory

Researchers in various fields have further refined and improved the SECI theory, integrating their expertise and research needs. For example, Chen Yewu (2005) subdivided tacit knowledge into actionable embodied knowledge and self-transcendent knowledge based on aesthetic appreciation, proposing a triple spiral model of knowledge creation with nine knowledge conversion modes. Gao Zhangcun and Tang Shukun (2008) combined cognitive psychology with SECI theory, introducing grey knowledge as a transition between explicit and tacit knowledge, and developed the IMCM model. Peng Can and Hu Houbao (2008) broke the knowledge dichotomy from a systematic perspective, innovating the BaS-C-SECI theory to address the challenge of integrating diverse background knowledge into the classic SECI theory and creating commonly accepted knowledge. Zhao Rongying, Liu Zhuozhu, and Wang Junling (2020) analyzed the classic SECI theory, pointing out that socialization or combination modes cannot directly achieve knowledge conversion, and developed the knowledge conversion space vector model to improve the knowledge conversion model. This paper adopts Ikujiro Nonaka and Hirotaka Takeuchi's theoretical perspectives, asserting that knowledge conversion involves four continuous processes: socialization, externalization, combination, and internalization. In the knowledge spiral theory, knowledge renewal is essentially a dynamic process of mutual transformation and promotion between tacit and explicit knowledge, arising from the conversion between different knowledge modes. In the information age, big data capabilities make the knowledge conversion process more convenient and explicit, accelerating knowledge renewal and promoting business model innovation.

Additionally, with global economic integration and the widespread application of internet technology, industry boundaries are blurring, and any creative business ideas and models will attract imitators. Business models are converging, reducing the advantages of innovative enterprises. The cross-border flow of capital, talent, and knowledge is accelerating, and entry barriers in some industries are decreasing. To survive and develop, enterprises have three options: become innovators of new business ideas, rapid imitators of new business models, or expand innovation space by "thinking globally, acting locally." Core competencies originate within enterprises and are characterized by value creation, heterogeneity, historical dependence, interrelatedness, difficulty in imitation and substitution, irreversible investment, and non-tradability. Resource development focuses on human intellectual industries and intangible assets. Western developed countries have entered the "intellectual" industrial era, with competitive advantage based on intellectual capabilities. Enterprises' intangible assets (such as talent, corporate culture, and values) become the source of sustainable competitive advantage. The lifecycle of tangible resources is shortening, leading many enterprises to invest in the cultivation of intellectual capital.

LITERATURE REVIEW

Hypothesis

The Impact of Big Data Capabilities on Knowledge Renewal

Knowledge-based theory posits that enterprises must leverage various resources to renew knowledge for sustained competitive advantage. The inherent vast data resources of enterprises provide an application environment for the development of big data capabilities. Enterprises with strong big data capabilities generally possess robust databases and comprehensive data analysis frameworks. They excel in constructing and maintaining knowledge bases, facilitating knowledge renewal (Hao et al., 2019), primarily in the following three areas.

Firstly, big data capabilities enhance knowledge screening. Knowledge screening involves refining fragmented knowledge content to capture the elements and usable knowledge that the enterprise truly needs. Big data insights can identify knowledge content aligned with the enterprise's development strategy, enabling more precise knowledge screening and effectively supplementing and enhancing the enterprise's knowledge base (Xiao Yanhong et al., 2017). For example, enterprises collect and crawl customer data based on customer knowledge themes, including transaction data, evaluation data, and access records. They use big data integration capabilities to process semi-structured and unstructured data and employ big data analysis capabilities to mine integrated data for valuable customer insights and identification.

Secondly, big data capabilities enhance knowledge integration. Knowledge integration is the process of merging externally acquired knowledge with existing enterprise knowledge based on knowledge type and structure (Wang Xiangyang et al., 2018). With big data analysis capabilities, highly similar knowledge is screened out and further integrated with existing competitor knowledge through association and cluster analysis, providing a knowledge foundation for the formulation of enterprise competitive strategies (Tang Bin et al., 2020).

Finally, big data capabilities can enhance knowledge application. Knowledge application is the process where enterprises further analyze and evaluate integrated knowledge to verify its effectiveness, providing innovative solutions for existing resource allocation and adding value to business operations (Paauw et al., 2018). Big data analysis capabilities can construct knowledge analysis models, enabling scientific and comprehensive evaluation of knowledge and verifying the value of new knowledge (Ye Yingping et al., 2019).

Based on this, this study will elaborate on the internal processes of knowledge renewal, namely knowledge screening, knowledge integration, and knowledge application, to explore the impact of big data capabilities on enterprise knowledge renewal, proposing the following hypothesis:

H1: Big data capabilities have a significant positive impact on knowledge renewal.

The Impact of Knowledge Renewal on Business Model Transformation

Faced with the complexity of external market knowledge, enterprises need to filter out the knowledge content that significantly impacts business model transformation, assess its advancement and future influence, and analyze the knowledge closely related to the enterprise's development strategy (Yang Gang et al., 2020). Based on knowledge screening, enterprises should integrate this knowledge with their existing knowledge systems, or innovate through combination, to optimize the current knowledge structure. New knowledge only gains significance when it is continuously embedded in business operation processes and management paradigms, thereby deriving value (Milosevic et al., 2018).

External knowledge from different sources differs significantly from existing enterprise knowledge in terms of structure, management practices, and organizational goals, increasing the difficulty of knowledge transfer. By linking external knowledge with existing knowledge based on content, differences, and problem-solving potential, enterprises can determine if the new knowledge can supplement or enhance the existing knowledge. This process helps form problem-solving ideas by connecting potentially useful knowledge.

For enterprises, knowledge renewal is not a simple addition of knowledge elements but a process of knowledge reconstruction, which is crucial for updating enterprise knowledge resources. Fully integrating internal and external knowledge helps maximize the value of enterprise knowledge, thereby enhancing organizational innovation capability (Mehrabani & Shajari, 2012).

For example, the key business activities of an enterprise often involve knowledge interactions between the enterprise and customers, partners, and different departments within the enterprise. When new external knowledge is accepted and processed into new knowledge by other entities within the enterprise's value network, this cross-boundary activity promotes the circulation of new knowledge within and between organizations, leading to process changes and the generation of new business activities. Therefore, knowledge renewal is the foundation of knowledge creation.

To respond to dynamically changing customer demands, enterprises create new knowledge through knowledge renewal, applying this new knowledge to change operational systems and business structures, aiming to achieve business model transformation. Therefore, the following hypothesis is proposed:

H2: Knowledge renewal has a significant positive impact on business model transformation.

The Impact of Big Data Capabilities on Business Model Transformation

This study posits that big data capabilities positively impact the three components of business models: value proposition, value creation, and value realization.

Firstly, big data capabilities can promote value proposition innovation. In the context of consumption upgrade, enterprises must enhance customer experience by deeply mining and analyzing massive user behavior data accumulated on platforms, uncovering the commercial value hidden behind the data, and providing decision support for enterprises to promptly seize business opportunities (Davenport, 2014). Utilizing big data insights can uncover deeper potential value needs of customers, perceive consumption trends, and create demand scenarios using digital technology to guide customer consumption, thereby achieving value proposition innovation.

Secondly, big data capabilities can enhance value creation. Big data insights can further explore changes in customer needs, providing decision guidance for enterprises to adjust their business strategies, ensuring other stakeholders follow up on products and services, and further exploring the potential value of partners to incentivize third-party innovation. This promotes the transformation of innovation activities into productivity and expands the scale of network effects (Perks et al., 2017), thereby enhancing enterprise value creation.

Finally, big data capabilities can enhance value realization. From a cost and revenue perspective, value realization exists in every element of value proposition and value creation. For example, in value proposition innovation, big data capabilities can enhance an enterprise's insight into market opportunities, bringing potential revenue (Brinch, 2020).

Based on the above analysis, this study proposes the following hypothesis:

H3: Big data capabilities have a significant positive impact on business model transformation.

The Impact of Knowledge Renewal on the Relationship Between Big Data Capabilities and Business Model Transformation

Enterprises use big data technology for full-sample data analysis, uncovering hidden patterns behind related data, which helps identify valuable knowledge. By repeatedly using these specific types of knowledge, enterprises can deepen their insights and understanding of such knowledge (Leiponen & Helfat, 2010). This process enhances the flow and integration of knowledge within the enterprise, promoting business model transformation.

Knowledge renewal plays a crucial connecting role between big data capabilities and business model transformation. Enterprises utilize big data technology for deep learning and repeated learning, fully exploring the rationality and potential between external knowledge and existing enterprise knowledge. Through knowledge deconstruction, they extract useful information, construct new knowledge structures through knowledge screening and integration, and achieve knowledge renewal propositions (Zhao et al., 2016).

Knowledge renewal enables enterprises to identify market opportunities early, accurately target markets, and engage in new business activities with partners, thus facilitating business model transformation. New knowledge, when embedded in product and service development, business operation processes, and management paradigms, helps derive value, emphasizing the significance of knowledge renewal for business model transformation. Big data capabilities facilitate knowledge renewal by evaluating knowledge, reducing the risk of knowledge conversion, removing outdated knowledge, and refining data analysis models, thereby supporting rapid business innovation and commercial model transformation.

Based on the above, the following hypothesis is proposed:

H4: Knowledge renewal mediates the relationship between big data capabilities and business model transformation.

The Moderating Role of Resource Slack on Knowledge Renewal and Business Model Transformation

Business model transformation not only relies on knowledge acquisition within the value network but also requires internal knowledge processing and restructuring (Yun Lexin et al., 2017). Knowledge renewal is a prerequisite for increasing the stock of enterprise knowledge (Ortiz et al., 2018). The results of knowledge renewal effectively guide business model transformation. Only by deconstructing external knowledge and effectively merging it with internal knowledge through continuous experimentation can enterprises create new knowledge and apply it to value proposition innovation, business process reengineering, new product and service development, and marketing channel restructuring. This process enables enterprises to overcome the bottleneck of business model transformation and change their development trajectory, thereby increasing the success rate of business model transformation (Wu Zengyuan et al., 2018).

According to the Resource-Based View (RBV) (Wernerfelt, 1984), enterprises need a certain level of resource reserves to obtain and maintain competitive advantage. Resource slack, characterized by excess resources, plays a significant role in supporting innovative behaviors, including business model transformation. Successful innovation in business models can lead to competitive advantages, and the presence of resource slack positively impacts the likelihood of successful business model innovation.

Moreover, when utilizing unique resources, enterprises can leverage additional resources that they do not own, providing more opportunities to access new perspectives and information relevant to their development. This capability enhances opportunity recognition and enables timely strategic adjustments, facilitating new business model transformations. Therefore, resource slack serves as a foundation for knowledge renewal, allowing enterprises to acquire market, channel, and policy information, and stay updated on industry trends, which is crucial for overcoming resource constraints and innovating business models.

Based on the above, the following hypothesis is proposed:

H5: Resource slack positively moderates the relationship between knowledge renewal and business model transformation.

The Moderating Role of Resource Slack on Big Data Capabilities and Business Model Transformation

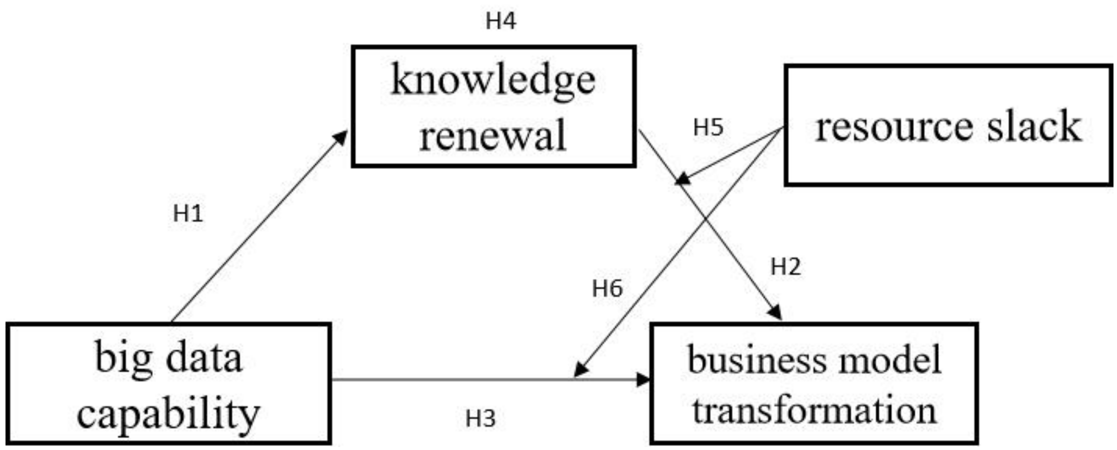
Enterprises can quickly acquire knowledge using big data capabilities, avoiding resource consumption and time wastage (Zhan et al., 2018). Big data capabilities integrate internal and external data resources, uncovering new business opportunities through analysis to adapt to changing external environments. Teece (2018) points out that in a constantly changing business environment, enterprises need to understand the resources and capabilities required for business model transformation. In a digital context, big data has become a key driver of enterprise survival and growth (Ghezzi & Cavallo, 2020). Enterprises have accumulated vast amounts of data driven by internet technology, but data alone does not confer a competitive advantage. It needs to be combined with other enterprise resources to form big data capabilities, which are fundamental to business model transformation (Li Wen et al., 2020).

This study posits that big data capabilities are crucial for enterprise survival and growth in a digital context and serve as the micro-foundation for business model transformation. Resource slack provides the basis for enterprise actions, enabling accurate market opportunity grasp and rapid response to market dynamics. Knowledge resources and relational resources offer advantages for innovation behaviors, playing a vital role in business model transformation.

Based on the above, the following hypothesis is proposed:

H6: Resource slack positively moderates the relationship between big data capabilities and business model transformation.

Figure 1 Study architecture diagram



Source: Prepared by the author (2024)

Sampling Methods and Data Collection

Data Collection

This study primarily investigates how managers utilize big data capabilities to facilitate knowledge renewal and subsequently achieve business model transformation. The empirical research focuses on enterprises in four regions of Jiangxi Province: Shangrao (East Jiangxi), Pingxiang (West Jiangxi), Ganzhou (South Jiangxi), and Nanchang (North Jiangxi). The selected enterprises span various industries, including technology and information, financial services, healthcare, manufacturing, retail, and energy. The primary respondents are senior management personnel from these companies. A set of sample selection criteria was established: enterprises must have a minimum of 50 employees, assets exceeding 5 million RMB, and be at least two years old. Smaller or younger companies are less likely to have the capacity for cross-organizational knowledge transfer and are thus less suitable for studying business model transformation.

Based on data provided by the official credit reporting agency under the China SME Development Sub-Fund (Tianyancha), the total number of enterprises in the four regions of Jiangxi Province is 2,322. The distribution is as follows: Shangrao 449, Pingxiang 296, Nanchang 801, and Ganzhou 776, accounting for 19.33%, 12.75%, 34.50%, and 33.42%, respectively. Following this distribution, questionnaires were allocated to ensure proportional representation.Using Dillman's(1978) formula:Ns=(Np)(p)(1-p)/[(Np-1)(B/C)2+(p)(1-p)]， the minimum required sample size Ns was calculated to be 384. The final distribution plan involved sending 800 questionnaires: 155 to Shangrao, 102 to Pingxiang, 276 to Nanchang, and 267 to Ganzhou. The survey commenced on November 5, 2023, and targeted senior managers (chairpersons, general managers, deputy general managers) who were knowledgeable about the company's operations and strategic planning. By January 10, 2024, 710 questionnaires were returned, with 579 valid responses after excluding invalid ones, resulting in an effective response rate of 81.55%. The valid responses were distributed as follows: 102 from Shangrao, 62 from Pingxiang, 219 from Nanchang, and 196 from Ganzhou.

To understand the structure of the effective sample, the study analyzed the samples based on four characteristics: industry, years of establishment, number of employees, and capital amount. In terms of industry, the samples were predominantly from manufacturing (79.79%), followed by technology and information (8.46%), energy (4.32%), financial services (3.80%), retail (2.42%), and healthcare (1.21%). This reflects the dominant position of manufacturing in the current economy. Regarding the number of employees, companies with 100-299 employees accounted for the highest proportion (35.75%), followed by 300-999 employees (30.05%), 50-99 employees (17.44%), and 1000-4999 employees (13.13%), indicating that medium-sized enterprises predominated. In terms of capital, companies with assets between 5-7.99 million RMB represented the largest share (64.59%), followed by those with 8-9.99 million RMB (27.98%), and those with 10 million RMB and above (7.43%), indicating that most companies had medium capital scales. Regarding company age, enterprises established for 5-10 years accounted for the highest proportion (33.68%), followed by 3-5 years (18.65%), 10-15 years (23.49%), 2-3 years (13.13%), and 15 years and above (11.05%). This suggests that most enterprises were in their growth or maturity stages. Overall, the sample covered multiple industries and various scales, providing a comprehensive basis for further research.

Measurement

This study employed validated scales from authoritative journals, using a five-point Likert scale proposed by Likert to ensure the validity and reliability of the items. A pre-survey was conducted with 100 enterprises. According to Wu (2010), a Cronbach's alpha value greater than 0.7 indicates high reliability.

The big data capabilities scale, developed based on Xie Weihong's (2018) research and adapted to the enterprises' practical situations, consisted of 12 items. The total Cronbach's alpha for big data capabilities was 0.961 (>0.7), with a CITC greater than 0.4. The business model transformation scale, drawing from Zott and Amit (2007) and Clauss (2017), consisted of 9 items, with a total Cronbach's alpha of 0.953 (>0.7) and an average CITC greater than 0.4. Knowledge renewal, measured based on Lawson's (2002) work, focused on product and service development using new knowledge. The total Cronbach's alpha for knowledge renewal was 0.927 (>0.7), with a CITC greater than 0.4. Resource slack, based on the scales of Tan et al. and Sun Jing et al., consisted of 9 items, with a total Cronbach's alpha of 0.947 (>0.8) and an average CITC greater than 0.4, indicating the scale's reliability.

The Cronbach's alpha values for all latent variables exceeded 0.7, and the CITC values exceeded 0.4, indicating that the scales were reliable and the items were relevant. Furthermore, comparing the total alpha value of the scales with the "delete alpha coefficient" showed no significant increase, suggesting that the items did not need modification or deletion and had good internal consistency (Wu, 2010).

Analysis and Results

This study employed SPSS 25.0 and Mplus 8.3 to establish a structural equation model to test the research hypotheses. The analysis followed Anderson and Gerbing's (1988) recommended two-step approach: first, evaluating the measurement model to verify the reliability and validity of the measurement data; second, testing the relationships between variables to validate the research hypotheses.

Reliability and Validity

Table 1 presents the results of the reliability and validity tests. The findings are as follows:

The KMO values exceed 0.7, ranging from 0.929 to 0.956. The Bartlett's test of sphericity is significant at the 0.000 level. According to Wu (2010), these results meet the KMO criteria, indicating that the variables are suitable for factor analysis.

The Cronbach's alpha coefficients for all variables are greater than 0.7, ranging from 0.910 to 0.964. This indicates high internal consistency and reliability of the scales used.The factor loadings for all items exceed 0.6, ranging from 0.707 to 0.848. These results meet Wu's (2010) criteria, demonstrating good validity of the scales.

According to the suggestion of Hu and Bentler (1995), the reference value of x2/df was less than 5, the reference values of CFI and TLI were greater than 0.90, and the reference values of RMSEA and SRMR were less than 0.08. The overall model fit indices are as follows: x2/df= 1.142 (less than 3), CFI and TLI values are both above 0.9, and RMSEA and SRMR values are both below 0.08. These results indicate that the model fits the data well.

Table 1 The reliability and validity test

Variable	Question items	The loading of factor	The alpha coefficient of Cronbach's α	KMO	P-value
	BDC1	0.805			
	BDC2	0.84			
	BDC3	0.842			
	BDC4	0.825			
BDC	BDC5	0.841	0.964	0.956	.000
	BDC6	0.817			
	BDC7	0.830			
	BDC8	0.836			
	BDC9	0.834			
	BDC10	0.821			
	BDC11	0.831			
	BDC12	0.848			
	KR1	0.827			
	KR2	0.843			
KR	KR3	0.816	0.929	0.929	0.000
	KR4	0.831			
	KR5	0.827			
	KR6	0.823			
	BMT1	0.745			
	BMT2	0.723			
	BMT3	0.762			
	BMT4	0.708			
BMT	BMT5	0.742	0.910	0.951	0.000
	BMT6	0.709			
	BMT7	0.719			
	BMT8	0.707			
	BMT9	0.725			
	RS1	0.815			
	RS2	0.812			
	RS3	0.822			
	RS4	0.845			
RS	RS5	0.824	0.950	0.943	.000
	RS6	0.831			
	RS7	0.808			
	RS8	0.829			
	RS9	0.833			

Notes:x2/df=1.142，CFI=0.993，TLI=0.993，RMSEA=0.016，SRMR=0.027.

Descriptive Statistics, Correlation Analysis and Common Method Differences

Descriptive Statistics and Correlation Analysis

Table 2 presents the data distribution, mean values, standard deviations, and Pearson correlation matrix for the study variables. The analysis shows that the absolute values of skewness for the variables range from 0.069 to 0.319, and the absolute values of kurtosis range from 2.217 to 2.777, indicating that the data meet the requirements for normal distribution (Zhu and He, 2004).Additionally, the composite reliability (CR) for the three latent variables is greater than 0.7, ranging from 0.910 to 0.964. The average variance extracted (AVE) values exceed 0.5, ranging from 0.529 to 0.691. Furthermore, the square root of the AVE values is greater than the corresponding Pearson correlation coefficients, conforming to the standards suggested by Wu (2010). The correlation coefficients are all greater than 0.6, and the AVE values are above 0.5, demonstrating that the scales possess strong convergent and discriminant validity.

Table 2 Reliability and validity of latent constructs, AVE and Correlation

	BDC	KR	RS	BMT
BDC	**0.831**			
KR	0.373	**0.828**		
RS	0.12	0.179	**0.825**	
BMT	0.366	0.388	0.123	**0.727**
Average value	3.473	3.164	3.494	3.667
Skewness	-0.274	-0.069	-0.298	-0.319
Kurtosis	2.466	2.217	2.367	2.777
SD	0.915	0.948	0.909	0.738
CR	0.964	0.929	0.95	0.91
AVE	0.691	0.686	0.68	0.529

Notes: $*p < 0.05$, $**p < 0.01$, $***p \leq 0.001$; the italic value is the arithmetic square root of AVE; the off-diagonal elements are the variable correlations. Source: Prepared by the author (2024)

Common Method Bias

Because all measures were collected in the same survey instrument, univariate tests were needed to address common methodological differences. In this pap, that most commonly used Harman single factor analysis method is use. In Table 3, the explained variance value of the first principal component before rotation is 13.518%< 40%, indicating that the common method bias test is passed (Wu, 2010).

Table 3 Common method bias test

Ingredient	Initial eigenvalue	% of variance	Cumulative%	Extract the square	% of variance
1	6.218	13.518	42.43	6.218	13.518
2	5.844	12.704	55.134	5.844	12.704
3	3.643	7.92	63.055	3.643	7.92
4	2.788	6.061	69.116	2.788	6.061

Source: Prepared by the author (2024)

Structural Equation Model Analysis

Direct Effect Analysis

Before examining the mediation variables, the path coefficients of the independent variables on the dependent variables are reported. The comprehensive model consists of three sub-models. Model 1 regresses business model transformation on big data capabilities. Model 2 regresses knowledge innovation on big data capabilities. Model 3 regresses business model transformation on knowledge innovation. The model fit indices indicate a good fit, with $\chi^2/df = 1.142$ (less than 3), CFI and TLI values above 0.9, and RMSEA and SRMR values below 0.08.

Table 4 shows that in the direct effect models (Models 1, 2, and 3), all independent variables significantly influence the dependent variables. Specifically, big data capabilities significantly influence knowledge innovation ($\beta = 0.331$, $t = 7.483$, $p = 0.000 < 0.05$), thus confirming hypothesis H1. Knowledge innovation has a significant positive impact on business model transformation ($\beta = 0.331$, $t = 8.328$, $p = 0.000 < 0.05$), supporting hypothesis H2. Li et al. (2022) also demonstrated that knowledge sharing impacts business model innovation through ambidextrous organizational learning, where both exploratory and exploitative learning positively influence innovative business models. Big data capabilities significantly influence business model transformation ($\beta = 0.326$, $t = 7.179$, $p = 0.000 < 0.05$), thereby validating hypothesis H3. Big data capabilities significantly impact business model transformation by providing deep insights and highly personalized analyses from vast information. This ability allows companies to redefine value creation and customer interaction through data-driven decision-making, thereby driving a shift from product-centric to customer-centric models.

Analysis of Mediating Effect

This study constructs a mediation effect model of knowledge innovation on big data capabilities and employs the Bootstrap method (Wang Mengcheng, 2014; Wen Zhonglin & Ye Baojuan, 2014), a commonly used and robust method in academic research. The mediation effect was tested by resampling 5000 times and calculating the 95% confidence interval. In the analysis, if the confidence interval does not include zero, a mediation effect exists; if it includes zero, no mediation effect is present.

Table 4 Direct and mediated effects

Assume the path	Non-normalised path coefficient	Standard error	t	p	Normalised path coefficients	Boot LLCI	Boot ULCI
BDC-KR	0.336	0.045	7.467	0.000	0.315	0.424	0.248
KR-BMT	0.189	0.034	5.559	0.000	0.175	0.256	0.122
mediated effects（BDC-KR-BMT）	0.064	0.014	4.457	0.000	0.077	0.037	0.091
Direct effect（BDC-BMT）	0.205	0.039	5.306	0.000	0.249	0.129	0.281
mediated effects	0.130	0.035	3.714	0.000	0.142	0.199	0.061
Direct effect	0.362	0.071	5.099	0.000	0.397	0.501	0.223
Total indirect effect:	0.492	0.048	10.283	0.000	0.598	0.398	0.586

Notes: *p < 0.05, **p < 0.01, ***p < 0.001. Source: Prepared by the author (2024)

In Table 4, the output of the mediation effect analysis includes total effects, direct effects, and total indirect effects. The bootstrap sampling method was employed to examine the mediation effects.

Table 4 indicates that the mediation effect value for the pathway "Big Data Capabilities - Knowledge Innovation - Business Model Transformation" is 0.064, with a 95% confidence interval ranging from 0.037 to 0.091, not including 0, and the p-value is less than the significance level of 0.05. This suggests the presence of a mediation effect. When the mediation variable is added to the model, the independent variable significantly affects the dependent variable, indicating partial mediation (Wen Zhonglin & Ye Baojuan, 2014). Thus, hypothesis H4 is supported. Knowledge innovation plays a significant partial mediation role between big data capabilities and business model transformation. Knowledge innovation serves as a crucial mediator between big data capabilities and business model transformation, a finding supported by several studies. According to Ciacci and Penco (2024), firms innovate their business models by developing big data analytical capabilities, especially in competitive environments. This study highlights the importance of the dynamic capabilities perspective in business model innovation, emphasizing the integration of digital technologies to improve internal activities and customer interactions (Teece et al., 2016; Matarazzo et al., 2021). Therefore, knowledge innovation bridges big data technology and business model innovation, accelerating organizational responses to market changes and enhancing competitiveness and sustained innovation, consistent with the results of this study.

Analysis of the Moderating Effect

This study employs a latent moderated structural equations method to test the role of moderation variables. When the standardized coefficient of interaction is $P < 0.05$, it indicates a significant moderation effect (Kelava et al., 2011). Model 1 uses knowledge innovation as the independent variable, resource slack as the moderation variable, and business model transformation as the dependent variable. Model 2 uses big data capabilities as the independent variable, resource slack as the moderation variable, and business model transformation as the dependent variable.

Model 1: Testing the Moderation Effect

The model fit measures for the moderation effect in Model 1 are as follows: $\chi^2/df = 1.164$ (less than 5), indicating good fit; SRMR = 0.026, RMSEA = 0.017 (less than 0.08), indicating ideal fit; TLI = 0.993, CFI = 0.993 (both above 0.9), indicating ideal fit. Table 5 shows that the standardized coefficient of knowledge innovation * resource slack on business model transformation is 0.319 ($t = 7.572$, $p = 0.000 < 0.05$), indicating a significant moderating effect of resource slack between knowledge innovation and business model transformation. Therefore, hypothesis H5 is supported.

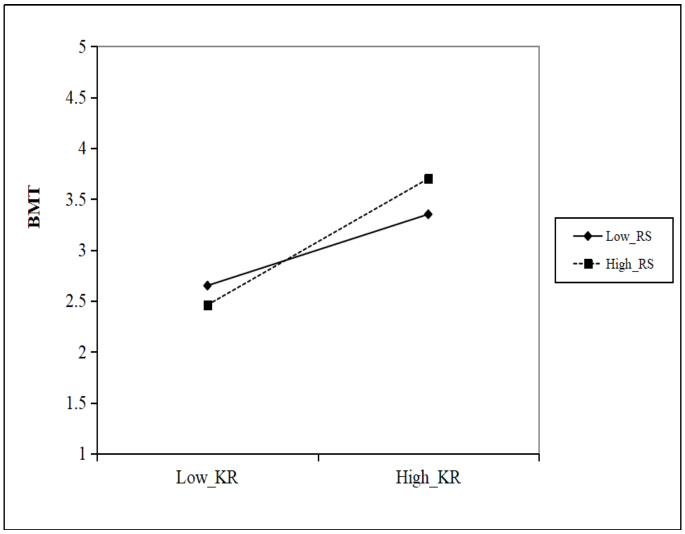
Table 5, Moderation Effect Analysis for Resource Slack between Knowledge Innovation and Business Model Transformation

Variable relationship	Non-normalised path coefficient	Standard error	t	p	Normalised path coefficients	Boot LLCI	Boot ULCI
KR-BMT	0.324	0.035	9.352	0.000	0.421	0.255	0.393
RS-BMT	0.051	0.033	1.526	0.127	0.061	-0.014	0.116
KR*RS-BMT	0.270	0.036	7.572	0.000	0.319	0.199	0.341

Source: Prepared by the author (2024)

To further investigate the moderating effect of resource slack on the relationship between knowledge innovation and business model transformation, this study employed structural equation modeling to visualize the pathway results. As the moderating variable, resource slack, increases, the degree of the independent variable, knowledge innovation, also increases, leading to a greater extent of the dependent variable, business model transformation ($\beta = 0.319$, $t = 7.572$, $p = 0.000$). This indicates that the characteristic of resource slack positively moderates the impact of knowledge innovation on business model transformation.

Figure 2 The Moderating Effect of Resource Slack on the Relationship Between Knowledge Innovation and Business Model Transformation



Source: Prepared by the author (2024)

Model 2: Moderating Effect Test

The fit indices for the moderating effect model (Model 2) are as follows: the χ^2/df value is 1.164, which is less than 5, indicating a good fit. The SRMR value is 0.026, and the RMSEA value is 0.017, both of which are below the threshold of 0.08, indicating an ideal fit. The TLI and CFI values are both 0.993, exceeding the benchmark of 0.9, further supporting the model's good fit. Table 6 demonstrates that the standardized coefficient for the interaction term between big data capability and resource slack on business model transformation is 0.303 ($t = 7.202$, $p = 0.000 < 0.05$). This indicates that resource slack significantly moderates the relationship between big data capability and business model transformation, thereby confirming hypothesis H6.

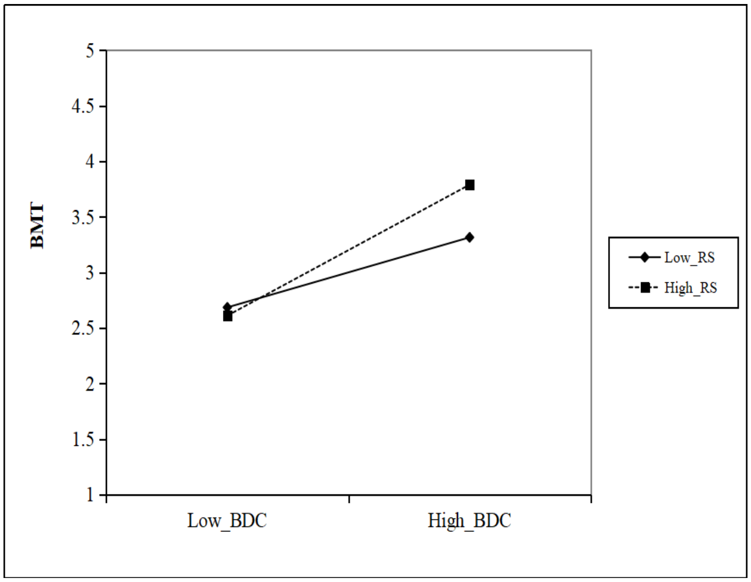
Table 6 Testing the Moderating Effect of Resource Slack on the Relationship between Big Data Capability and Business Model Transformation

Variable relationship	Non-normalised path coefficient	Standard error	t	p	Normalised path coefficients	Boot LLCI	Boot ULCI
BDC-BMT	0.315	0.036	8.774	0.000	0.382	0.244	0.386
RS-BMT	0.089	0.033	2.660	0.008	0.107	0.024	0.154
BDC*RS-BMT	0.274	0.038	7.202	0.000	0.303	0.2	0.348

Source: Prepared by the author (2024)

To further investigate the moderating effect of resource slack on the relationship between big data capability and business model transformation, this study employed a structural equation modeling (SEM) approach to plot the moderating effect model. The results indicate that as the value of the moderating variable, resource slack, increases, the impact of the independent variable, big data capability, on the dependent variable, business model transformation, also becomes more pronounced ($\beta=0.303$, $t=7.202$, $p=0.000$). Therefore, resource slack positively moderates the relationship between big data capability and business model transformation, enhancing the effect of big data capability on business model transformation.

Figure 3 Moderating Effect of Resource Slack on the Relationship Between Big Data Capability and Business Model Transformation



Source: Prepared by the author (2024)

CONCLUSIONS AND DISCUSSION

In the context of globalization and informatization, the importance of big data capabilities has become paramount. Enterprises can leverage cross-border collaborations to gain more market insights and technological resources, thereby driving business model transformation and innovation (Schilling & Steensma, 2001). Grounded in the theories of knowledge spiral and core competence, with knowledge renewal as an intermediary perspective, this study reveals the significance of crossing organizational boundaries in promoting business model transformation. Specifically, the following conclusions can be drawn:

Firstly, big data capabilities effectively promote enterprise business model transformation. As a core strategic resource of modern enterprises, big data capabilities are facilitating significant changes and innovations in business models. Initially, these capabilities enable enterprises to extract valuable information and insights from vast amounts of data, thereby enhancing their understanding of market trends, consumer behaviors, and competitive environments. For example, through big data analytics, enterprises can identify demand differences in various market segments, predict future market trends, and accordingly adjust product and service strategies to enhance market responsiveness (Chen et al., 2021). Moreover, big data capabilities support precise marketing by analyzing consumer purchasing behaviors and preferences, enabling enterprises to formulate personalized marketing strategies that enhance customer experience and satisfaction (Wang & Li, 2022). Secondly, big data capabilities improve operational efficiency and decision-making within enterprises. Real-time data monitoring and analysis allow for optimized resource allocation and reduced operational costs. For instance, in supply chain management, big data analysis helps predict inventory needs, streamline supply chain processes, and minimize inventory backlog and logistics costs (Liu et al., 2022). In production, data from equipment analysis predicts equipment failures, enables preventive maintenance, reduces downtime, and increases production efficiency (Zhang & Zhao, 2023). Furthermore, big data capabilities drive innovation in enterprise business models. Not only do they enhance efficiency and responsiveness in existing operations, but they also lay the foundation for developing new business models. For instance, shared economy models, on-demand customized services, and platform-based business models benefit from big data technology. By analyzing data, enterprises accurately grasp user needs, swiftly adjust business strategies, and develop new profit models (Li et al., 2022). Additionally, big data capabilities promote cross-border cooperation and ecosystem development within enterprises. Through data sharing, companies collaborate with partners to develop new products and services, complement resources and capabilities, and jointly build open, collaborative business ecosystems (Yang & Chen, 2021).

Secondly, enhancing knowledge renewal effectively strengthens the impact of big data capabilities on business model transformation. This process is not only about maintaining competitiveness but also about crossing organizational boundaries and enhancing innovation capabilities. Through continuous knowledge updating and application, organizations can effectively strengthen their big data capabilities. Initially, knowledge renewal enables organizations to respond more quickly to changes in the external environment. With rapid technological and market demand evolution, traditional organizational boundaries no longer suffice in complex business environments. By introducing new knowledge and technologies, organizations can break these boundaries and achieve cross-departmental and cross-industry collaborative innovation (Rerup & Feldman, 2023). Secondly, by combining knowledge renewal with big data analysis, organizations can innovate their business models. These new models are not only based on market demand and customer feedback but also optimized and expanded using data-driven methods. For example, enterprises can accurately formulate personalized product and service strategies by analyzing customer data and market trends, thereby enhancing customer satisfaction, loyalty, and further expanding market share and revenue (Pavlou & El Sawy, 2021). Most importantly, this transformation involves not only technological updates but also comprehensive reshaping of organizational strategies and operational methods. Successful organizations must not only maintain leadership in technology but also ensure effective integration and application of new technologies and knowledge into daily operations (Rerup & Feldman, 2023).

Research Recommendations

Future research should further explore the complex relationship between big data capabilities, knowledge renewal, and business model transformation. Firstly, longitudinal research designs are recommended to track the evolution of enterprise transformation over the long term, revealing the dynamic impact of these factors on business model transformation at different stages (Zhu et al., 2024). This longitudinal approach can help scholars better understand the temporal dynamics of organizational behavior.

Secondly, experimental studies and simulation models can explore the mechanisms of big data capabilities and business model transformation under different contexts. For instance, by simulating different market environments and internal organizational structures, researchers can study the impact of these factors on business model transformation in various contexts. This will provide more precise empirical support for theoretical development and offer specific contextual guidance for enterprise practices (Cenamor et al., 2019).

Lastly, future research should focus on the impact of technological advancements and market changes on big data capabilities. For example, with the development of emerging technologies such as artificial intelligence and blockchain, understanding how these technologies affect big data capabilities and subsequently drive business model transformation is an important area for in-depth exploration (Huang et al., 2022). By studying the impact of emerging technologies on organizational behavior and business models, scholars can provide forward-looking guidance for enterprises to address future technological changes.

Limitations

This study has discussed the role of big data capabilities in business model transformation to a certain extent, but it also has limitations. Firstly, the study collected data through self-assessment by management executives, who evaluated organizational boundary crossing, business model transformation, and knowledge renewal behaviors. This approach may have been influenced by subjective factors, potentially affecting the accuracy of the data. Secondly, the study focused on enterprises in six industries across four regions in Jiangxi Province, namely Shangrao, Pingxiang, Nanchang, and Ganzhou. This limited scope may not fully represent other regions and types of enterprises, each of which may differ in characteristics and nature, potentially influencing the study's results. Finally, there are limitations in terms of time dimension. The study primarily used cross-sectional data for analysis, which, while revealing relationships between variables, cannot capture the dynamic processes of variables over time (Ployhart & Vandenberg, 2010). Future research could employ longitudinal research designs to track enterprise transformation processes over the long term, thereby revealing the dynamic impact of organizational boundary crossing on business model transformation at different stages (Rindfleisch et al., 2008).

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