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Big Data Capabilities as Strategic Assets: Enterprise Value Creation Mechanisms in 33 Studies

Qing Cao [1], Yanhua Xu [1], Jin Luo [1,2,*], Li Fan [3] and Yonghui Ni [1]

[1] School of Geography and Environment, Jiangxi Normal University, Nanchang 330022, China; 202340100091@jxnu.edu.cn (Q.C.); yanhuaxuedu@foxmail.com (Y.X.); yonghuini@foxmail.com (Y.N.)
[2] Key Laboratory of Poyang Lake Wetland and Watershed Research, Ministry of Education, Jiangxi Normal University, Nanchang 330022, China
[3] Faculty of Education, College of Teacher Education, East China Normal University, Shanghai 200062, China; 15283199471@163.com
* Correspondence: luojin@jxnu.edu.cn

Abstract

Background: Big data capability is a core strategic asset for enterprises, but existing studies on its relationship with enterprise value creation are fragmented, with inconsistent effect magnitudes and boundary conditions. This meta-analysis synthesized empirical evidence to clarify their overall relationship and the moderating roles of antecedent, mediating, and outcome variables. **Methods**: A systematic search (ending July 2025) across seven databases (CNKI, Web of Science, etc.) identified thirty-three empirical studies meeting criteria (clear sample size, correlation coefficients). Following PRISMA 2020 and OSF registration, two researchers extracted data independently. CMA 3.0 was used with a random effects model; effect sizes (Pearson's r), heterogeneity (Q, I^2), and publication bias (funnel plots, Egger's test) were analyzed. **Results**: Involving 14,993 samples, big data capability showed a moderately significant positive correlation with enterprise outcomes (r = 0.486, 95% CI: 0.408–0.557, $p < 0.001$) with high heterogeneity ($I^2 = 93.502$). Subgroup analyses revealed: learning orientation (r = 0.883) as the strongest antecedent; organizational agility (r = 0.631) and innovation (r = 0.595) as significant mediators (resource integration not significant); enterprise innovation performance (r = 0.730) as the top outcome. No publication bias was found (Egger's $p = 0.284$). **Conclusions**: Big data capability positively impacts enterprises, with learning orientation and innovation performance as key moderators. Enterprises should prioritize a learning culture and leverage organizational agility. Future research needs diverse samples and longitudinal designs to explore causality.

Keywords: big data capability; enterprises; meta-analysis; moderating variables

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Academic Editors: Adolfo Crespo Márquez and Vicente González-Prida

Received: 23 July 2025
Revised: 11 August 2025
Accepted: 17 August 2025
Published: 19 August 2025

Citation: Cao, Q.; Xu, Y.; Luo, J.; Fan, L.; Ni, Y. Big Data Capabilities as Strategic Assets: Enterprise Value Creation Mechanisms in 33 Studies. *Appl. Sci.* **2025**, *15*, 9142. https://doi.org/10.3390/app15169142

Correction Statement: This article has been republished with a minor change. The change does not affect the scientific content of the article and further details are available within the backmatter of the website version of this article.

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1. Introduction

The continuous development of big data has had a great impact on the development process of enterprises, and many enterprises have begun to recognize that big data will become the future development trend and the key to competition [1–5]. Big data capabilities have the "potential to change management theory and practice" [6], which has been hailed as the next "management revolution", and research on the impact of big data capabilities on various aspects of enterprises has received extensive attention from academia and society [7]. The competition of enterprises in the big data environment is the competition of information, data, and knowledge [8], so exploring the cultivation mechanism of big data capability of modern enterprises in the big data environment has important theoretical

and practical significance [9]. At present, big data technology has penetrated various industries, and enterprises, as the key source and applicator of big data, making efficient use of big data to promote innovation, transformation, and upgrading, which has become an important trend for the future development of industries [10–12]. In the context of the new era, understanding big data capability and how to mine the value from it and effectively apply it to the enterprise development strategy is an important and urgent issue for entrepreneurs and managers [13–15].

Big data capability has a very important role for enterprises, but the process of the role is very complex, involving multiple aspects of data collection, processing, analysis, mining, and application [16,17]. Therefore, enterprises need to recognize the importance of big data and how big data capabilities can help them develop, and in what ways they can support the construction and application of big data capabilities. Different enterprises will interact with big data capabilities in different ways to solve different types of problems and maximize the impact of big data capabilities [18,19]. By constructing a "data-information-knowledge-value" transformation model, Liu demonstrated that big data can significantly enhance marketing efficiency and deepen customer insights through integrating internal and external data (such as demographic statistics and consumption behavior), while exploring deep characteristics such as behavior and life cycle stage can greatly improve marketing efficiency, deepen customer insight, drive accurate decision-making, and value creation. Some studies show that big data capabilities have a positive impact on the innovation performance of enterprises, but the differentiated impacts on the mechanism in different internal and external contexts should not be ignored [20,21]. At the same time, there are also studies showing that big data capabilities have a series of negative impacts on enterprises, and big data capabilities can be exploited by unscrupulous elements in a reverse way, thus bringing serious harm to the economy and society [22].

To sum up, the relationship between the role of big data capabilities and enterprises is not clear; enterprises have been an important carrier of social and economic development, and it is still debatable whether enterprises can develop through the support of big data capabilities. Based on this, this study adopts a meta-analysis approach to explore the following questions.

H1. *How do big data capabilities affect enterprises?*

H2. *Are big data capabilities influenced by antecedent variables while affecting enterprises' development?*

H3. *Are big data capabilities affected by mediating variables while affecting enterprises' development?*

H4. *Are big data capabilities affected by outcome variables while affecting enterprises' development?*

2. Materials and Methods

2.1. Search Strategy

Meta-analysis is a research method that combines the results of multiple independent studies with the same research objective [23–25], and meta-analysis of controversial or even contradictory similar studies can lead to clearer conclusions. Therefore, this study adopts meta-analysis to analyze the impact of big data capabilities on enterprises, extracts relevant sample sizes by reading the literature, etc., compares and combines the results of experimental studies in similar fields, and calculates the magnitude of its effect size by adopting the correlation coefficient as the effect value.

The meta-analysis tool CMA was chosen for data integration and analysis. This software can be used for meta-analysis of both dichotomous and continuous variables and

can help to obtain forest plots (with effect sizes, confidence interval ranges, heterogeneity test values, etc.), funnel plots, etc., [26,27].

This systematic review and meta-analysis were conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and followed the recommendations of the Cochrane Handbook for Systematic Reviews. This systematic review and meta-analysis were registered in the Open Science Framework (OSF) under the digital object identifier https://doi.org/10.17605/OSF.IO/PNU5R.

Conducting a meta-analysis requires a literature search and systematic review to determine the feasibility of the study. In this study, we conducted literature searches on big data capabilities across seven databases: China National Knowledge Infrastructure (CNKI), Wanfang Data, VIP Chinese Journal Service Platform (VIP), Web of Science, ProQuest, EBSCO and Scopus databases, respectively. Using keywords such as "Big data capability" and "enterprise" (including terms like big data, big data analysis, big data management, big data adoption, data-driven capability, establishment, business, company, and firm), we performed title, abstract, and keyword searches. Experimental studies were identified through keyword filters including "empirical research", "sample size", and "correlation analysis". To ensure comprehensive coverage, we executed multiple searches using different combinations of these keywords. Please see Appendix A for the example of specific search equation. The search deadline is set to July 2025. The initial search yielded 14,993 results, from which 114,880 articles were retained after removing duplicates.

2.2. Eligibility Criteria

The literature was manually reviewed based on predefined inclusion criteria. Literature was screened based on the following criteria: (1) the research scenario, which must be related to enterprises; (2) the research question must be the impact of big data capabilities on enterprises, and at least one impact factor must be derived from the article; (3) the type of research must be an empirical study, which excludes literature such as theoretical studies, review papers, and so on; (4) the data of the study must be complete and explicitly report the sample size, the correlation coefficient, or a statistical quantity that can be converted into a correlation coefficient.

The search strategy identified 14,993 potentially relevant studies. After preliminary screening of titles and abstracts, 14,810 records were excluded. We conducted full-text screening on the 183 retrieved articles, as shown in Figure 1, with 33 studies ultimately included in the systematic review. The selection process is illustrated in Figure 1, followed by the PRISMA 2020 guidelines.

2.3. Literature Screening and Data Extraction

Reliable coding is a very important point in meta-analysis, and all studies should be assessed by at least two researchers. Therefore, the coding of variables in this exercise was conducted by two researchers independently. After developing the coding rules, the two researchers read all the selected papers and coded them independently. After the coding was completed, the two researchers compared the coded content and discussed the papers with discrepancies until a final, consistent code was developed. The codes used in this paper record the most important study characteristics and are divided into two parts: study description and effect size information. The description of the study includes a list of authors, year of publication, journal of publication, and name of the variable, while the effect size information includes the correlation coefficient of the variable and the antecedent variable.

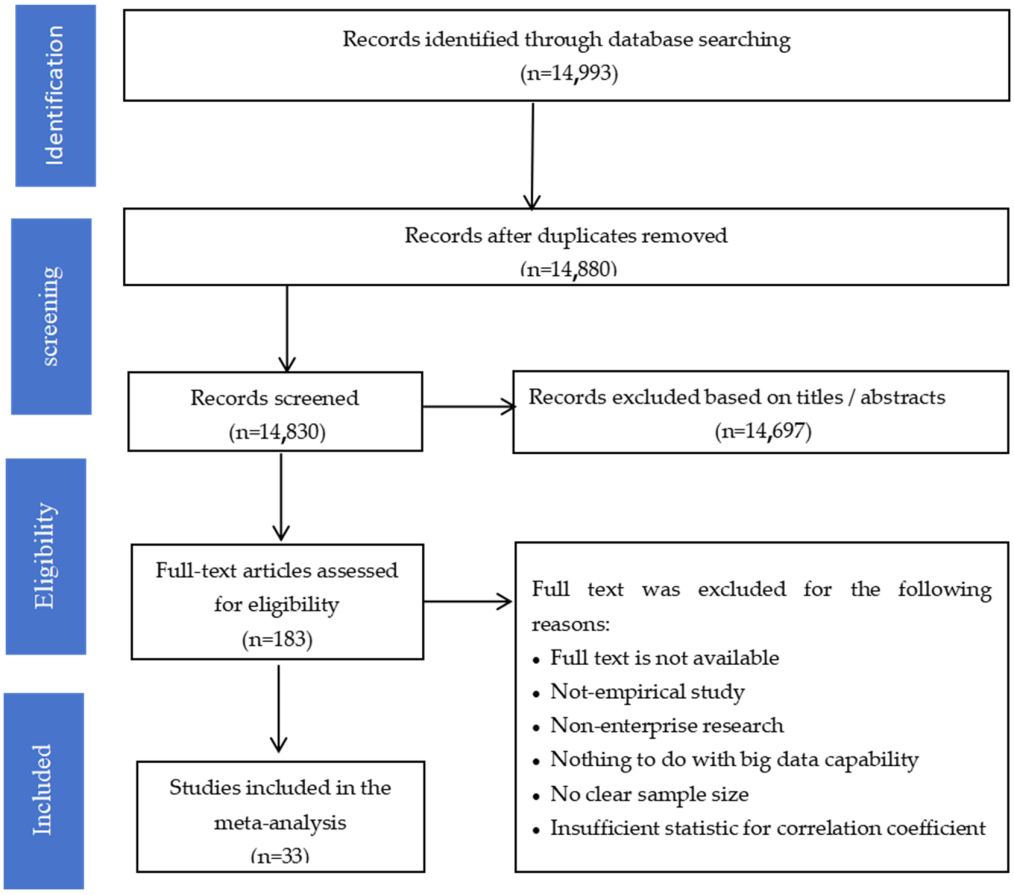

Figure 1. Flowchart of article selection.

Table 1 provides a summary of the results of the studies included in the final review, detailing information on authors, year, correlation coefficients, sample size and influencing factors.

Table 1. Review of Research on the Interaction between Enterprises and Big Data Capabilities.

Author	Year	Sample Size	r	Ex-Dependent Variable	Meta Variable	Outcome Variable
MinghuiCheng	2015	143	0.462	Others	Others	Business Model Innovation
TianhuiWang	2015	118	0.192	Others	None	Group Control Relationship
WeihongXie	2016	118	0.192	None	Resource Integration	Group Control Relationship
FanWu	2017	234	0.600	None	Supply Chain Resilience	Enterprise Performance
WeihongXie	2018	198	0.452	Top Management Support	Others	Business Model Innovation
DiXu	2018	205	0.786	Learning Orientation	None	Business Model Innovation
YifuTian	2019	249	0.516	Others	None	Business Model Innovation
YuqiaoHong	2019	131	0.434	None	Organizational Learning	Innovation Performance
YanZhang	2020	23	0.452	Environmental Dynamism	None	Innovation Performance
ZepengCai	2020	159	0.530	None	Knowledge Integration	Innovation Performance
YingChen	2020	74	0.700	Others	Innovation	Enterprise Performance

Table 1. *Cont.*

Author	Year	Sample Size	r	Ex-Dependent Variable	Meta Variable	Outcome Variable
ShanyuWang	2020	292	0.606	None	Organizational Learning	Business Model Innovation
JianfaZhou	2020	241	0.700	Strategic Orientation	None	Enterprise Performance
XueFeng	2020	272	0.810	Learning Orientation	None	Business Model Innovation
HaiyanZheng	2021	403	0.290	None	Knowledge Integration	Innovation Performance
YufengWang	2021	403	0.290	None	Knowledge Integration	Innovation Performance
XiaodanLi	2021	291	0.408	Top Management Support	None	Enterprise Performance
QiDong	2021	261	0.488	Strategic Orientation	Innovation	Enterprise Performance
YanZhang	2022	256	0.770	Environmental Dynamism	Innovation	Innovation Performance
LipingZhai	2022	274	0.484	Environmental Dynamism	Others	Enterprise Performance
YuyanLiu	2022	237	0.492	Environmental Dynamism	Organizational Agility	Innovation Performance
YanSong	2022	272	0.240	None	Knowledge Integration	Innovation Performance
ZhaojieWang	2022	128	0.505	None	Resource Integration	Innovation Performance
PeipeiSu	2022	277	0.584	None	Knowledge Integration	Business Model Innovation
HechengWang	2022	285	0.216	Others	Others	Business Model Innovation
MengshaZhou	2023	232	0.452	None	Supply Chain Resilience	Supply Chain Performance
ZewenChen	2023	209	0.240	Environmental Dynamism	Innovation	Enterprise Performance
PingLi	2023	658	0.531	None	Knowledge Integration	Enterprise Innovation Performance
NaLi	2024	202	0.510	Learning Orientation	Organizational Agility	Business Model Innovation
CancanJin	2024	468	0.504	Environmental Dynamism	Knowledge Integration	Business Model Innovation
XinZhang	2024	216	0.742	Environmental Dynamism	Others	Enterprise Performance
ZiweiHe	2024	371	0.803	Environmental Dynamism	Organizational Agility	Enterprise Innovation Performance
JieZhang	2025	478	0.087	Environmental Dynamism	Supply Chain Resilience	Supply Chain Performance

2.4. Data Analysis

All analyses in this study were completed in Comprehensive Meta-Analysis 3.0 software (CMA). CMA, as a stand-alone software program, contains a wide range of computational options, which can help researchers to comprehensively analyze and process the data from multiple studies [28]. Taking into account the characteristics of the experimental data in this study, the correlation coefficient (correlation, r) was chosen as the effect size, which is a statistical measure that describes the strength and direction of the linear relationship between two variables. In meta-analysis, the correlation coefficient usually refers to Pearson's correlation coefficient, which is calculated as follows:

$$r = \frac{\sum [(x_i - \overline{x})][y_i - \overline{y}]}{\sqrt{\left[\sum (x_i - \overline{x})^2 * \sum (y_i - \overline{y})^2\right.}} \quad (1)$$

where x_i and y_i denote the observed values of the two variables in each study, $\overline{x}$ and $\overline{y}$ denote the mean values of the two variables, respectively. The correlation coefficient ranges from -1 to 1. From a directional perspective, when the correlation coefficient r is positive, it indicates a positive correlation between variables (where an increase in one variable leads to an increase in the other, such as the positive relationship between supply quantity and

price in enterprises). When r is negative, it reflects a negative correlation between variables (where an increase in one variable leads to a decrease in the other, such as the inverse relationship between consumer demand and price). From the perspective of intensity dimension, the closer the absolute value of the correlation coefficient is to 1, the stronger the degree of linear correlation between variables; when the absolute value approaches 0, it indicates that the linear relationship between variables is weak or there is no significant linear correlation. In meta-analyses, correlation coefficients can be used to assess whether there is consistency in effect sizes across studies and whether the magnitude and direction of effect sizes are as expected.

3. Results

3.1. Overall Effect Test

3.1.1. Main-Effect Analysis

As shown in Figure 2, the main effects results show that the combined effect value of big data capability and enterprise r is 0.526 with a 95% confidence interval of (0.461, 0.585), which does not contain 0, in the random effects model. The big data capability and enterprise effects are significantly correlated under the 95% * confidence interval, which indicates that the main effect value is significant and H1 is supported. The main effect correlation coefficient value in this paper is between 0.3 and 0.5, indicating that big data capability has a significant positive medium-strength correlation with the enterprise. This result confirms the findings of previous studies that big data capabilities are strongly correlated with enterprises and provides empirical evidence for the subsequent implementation of digital innovation strategies in enterprises [29].

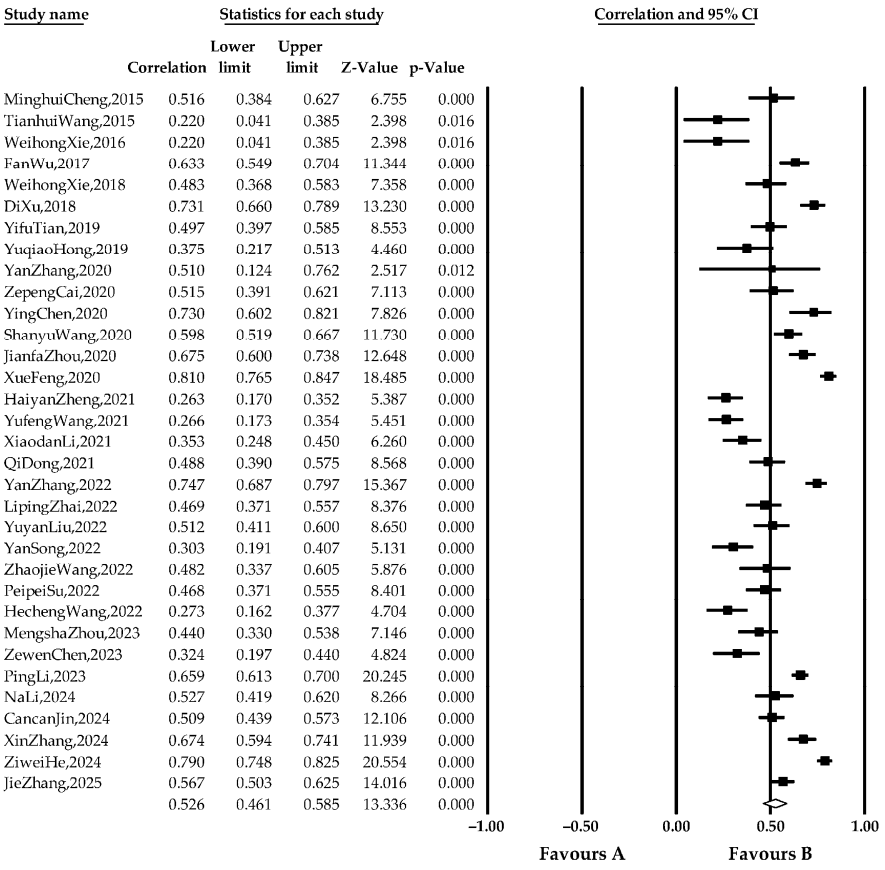

Figure 2. Forest plot.

3.1.2. Heterogeneity Test

In this paper, the sample as a whole is tested for heterogeneity. The Q-value statistic is a commonly used statistical indicator to test the degree of heterogeneity [30], and as can be seen from Table 2, the Q-value of the overall sample in this paper is 401.700 ($p = 0.000 < 0.001$), which is much larger than the value of $x^2_{0.05}$ (33) (84.821), and exceeds the corresponding degrees of freedom at $\alpha = 0.05$ chi-square value, indicating the existence of heterogeneity among the study samples. The I^2-statistical indicator then tests the proportion of the true difference in composition to the observed variation. Table 1 shows that the I^2 is 93.502, indicating that 93.502% of the observed variation in the meta-analysis is caused by the true difference in the effect values, which satisfies the requirement that the $I^2 > 0.6$, and it also indicates that there is heterogeneity in this paper, so it is necessary to select the random effects model to be corrected for further analysis [31]. At the same time, we analyze that the reasons for the heterogeneity may come from several aspects, such as antecedent variables and consequent variables of big data, so we need to carry out further tests on these moderating variables.

Table 2. Results of heterogeneity test.

Model	Effect Sizes and 95% Confidence Intervals				Heterogeneity				Tau-Squared	
	N	Est.	Lower	Upper	Q	df(Q)	*p*	I^2	Tau Squared	Standard Error
random	33	0.534	0.519	0.549	492.429	32	0.000	93.502	0.058	0.017
fixed	33	0.526	0.526	0.585						

3.1.3. Published Bias Test

Bias is the error between the result or inference value of a study and the true value [30], and publication bias is one of the main factors affecting the validity of the results in meta-analysis. Since there is not much sample data in this study, the funnel plot, Egger's test with loss of safety coefficient, is used to detect the bias in this study. When the Egger test is not significant, it indicates that the publication bias problem of the sample is not serious; or when the loss of safety coefficient $N > 5k + 10$, it also indicates that the publication bias problem of the sample is not significant.

As shown in Figure 3, the graph presents an inverted funnel shape, which is intuitive, with the horizontal axis representing the mean standard deviation effect value (Z-value) and the vertical axis representing the standard deviation of the effect value (standard error). Most of the effect values are relatively evenly distributed on both sides of the mean effect value and are concentrated towards the center line. The Egger test in this paper corresponds to a *p*-value of less than 0.05, implying the presence of publication bias, and vice versa. The result of the Egger test in this paper is $p = 0.284 > 0.05$. And the loss of the safety coefficient in this paper reaches 1807, which is much higher than the standard of the safety coefficient, and according to the principle of the safety coefficient method, when the loss of safety coefficient $N > 5k + 10$, it also indicates that the problem of publication bias in the samples is not significant. Therefore, the literature sample selected in this paper does not have a significant publication bias problem.

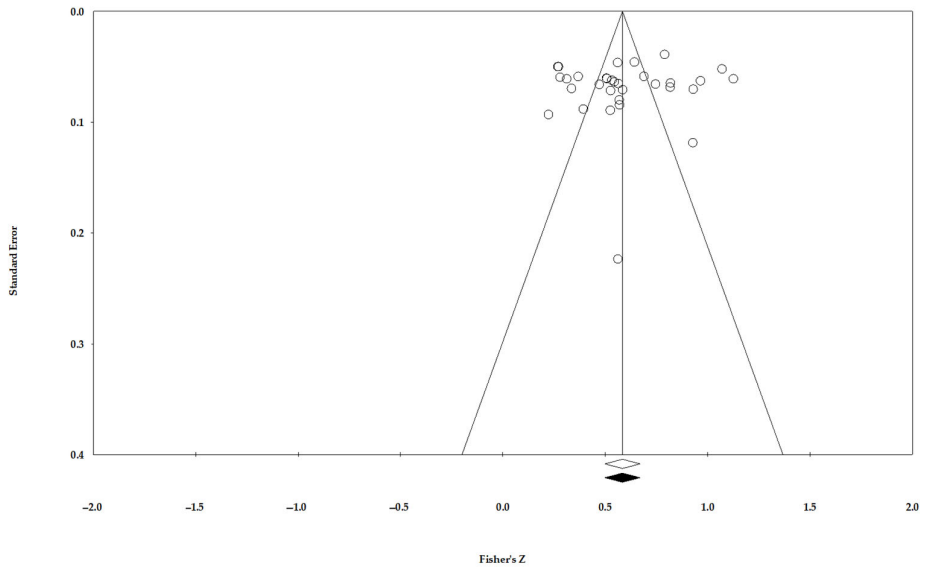

Figure 3. Funnel plot for all studies.

3.2. Regulation Effect Test

When we shift the focus of the study from the average effect to the difference itself, we need to start subgroup analysis, i.e., moderator variable analysis, on the basis of the categorical data. The results of the software analysis are shown in Table 2, revealing 4 independent variables and 6 outcome variables related to big data capabilities. Due to the significant Q value and I^2 greater than 0.6 for most of the data, the meta-analysis results were modeled using a random effects model. After the moderators were grouped, variables with k greater than or equal to 2 corresponding to each group were selected for meta-analysis. Some of the variables could not be grouped effectively, so they were combined as "other" to represent the results of subgroup analysis.

3.2.1. Different Precursor Variable Effects

The data in Table 2 show that big data competence and antecedent variables in general present a significant positive relationship and that multiple factors of antecedent variables are effective in promoting positive business development. The positive relationship between learning orientation (r = 0.883, $p < 0.001$) and big data capability is the strongest among all antecedent variables. Strategic orientation (r = 0.676, $p < 0.001$) has a significant positive effect on big data capability, indicating that strategic orientation can effectively promote the development of big data capability in enterprises. There is also a positive correlation between executive support (r = 0.443, $p < 0.001$), environmental dynamics (r = 0.677, $p < 0.001$), other (r = 0.499, $p < 0.001$), and big data capability. All three have a significant positive relationship with big data capability, and the strength of the relationship is not much different, which can significantly enhance the level of enterprise in big data capability. The relationship between learning orientation and big data competence is also positively correlated. Learning orientation also has a significant positive effect on big data capability.

3.2.2. Different Mediation Variable Effects

The data in Table 2 shows that big data capability and mediating variables generally show a non-significant positive relationship (r = 0.421, $p > 0.01$). However, Organizational agility (r = 0.631, $p < 0.001$), Innovate (r = 0.595, $p < 0.001$), supply chain elasticity (r = 0.552, $p < 0.001$), organizational learning (r = 0.500, $p < 0.001$), other (r = 0.492, $p < 0.001$), and knowledge integration (r = 0.438, $p < 0.001$) all showed significant positive correlations with

big data capability. The strength of positive correlations all showed a significant positive nature. Whereas, the relationship between resource integration (r = 0.359, $p > 0.01$) and big data capability is not significant.

3.2.3. Different Outcome Variable Effects

The data in Table 3 shows that big data capabilities and the outcome variables in general show a positive correlation with a significant relationship. The strength of positive correlations between Enterprise innovation performance (r = 0.730, $p < 0.001$), Business model innovation (r = 0.560, $p < 0.001$), Enterprise performance (r = 0.555, $p < 0.001$), and innovation performance (r = 0.453, $p < 0.001$) with big data capabilities all showed significant positive correlations in nature. While the relationship between group control (r = 0.220, $p < 0.001$) and big data capability showed a weak, positive, significant correlation.

Table 3. Summary of subgroup analysis results.

Sub-Group Analysis	Statistics of Each Group					Heterogeneity		
Group	**K**	**r**	**Z**	**95% CI**	***p*-Value**	**Q**	**df**	***p*-Value**
Ex-dependent variable						10.714	5	0.057
Learning orientation	3	0.883	5.540	[0.570, 1.195]	0.000 ***			
Strategic orientation	2	0.676	4.721	[0.395, 0.957]	0.000 ***			
Environmental dynamics	9	0.677	8.286	[0.517, 0.837]	0.000 ***			
Other	5	0.499	4.774	[0.294, 0.704]	0.000 ***			
Executive support	2	0.443	5.615	[0.288, 0.597]	0.000 ***			
None	12	0.483	7.515	[0.357, 0.609]	0.000 ***			
Meta variable						5.693	7	0.576
Innovate	4	0.595	4.377	[0.362, 0.759]	0.000 ***			
Supply chain elasticity	3	0.552	8.675	[0.328, 0.705]	0.000 ***			
Organize learning	2	0.500	3.720	[0.254, 0.685]	0.000 ***			
Other	5	0.492	5.942	[0.319, 0.538]	0.000 ***			
Knowledge integration	7	0.438	6.476	[0.294, 0.562]	0.000 ***			
Resources integration	2	0.359	2.489	[0.080, 0.586]	0.013			
Organizational agility	3	0.631	4.163	[0.374, 0.798]	0.000 ***			
None	7	0.579	5.133	[0.387, 0.722]	0.000 ***			
Outcome variable	33					33.228	5	0.000 ***
Innovative performance	9	0.453	5.752	[0.311, 0.575]	0.000 ***			
Group control relationship	2	0.220	3.392	[0.094, 0.339]	0.001 **			
Enterprise performance	8	0.555	8.381	[0.445, 0.648]	0.000 ***			
Enterprise innovation performance	2	0.730	6.628	[0.575, 0.835]	0.000 ***			
Supply chain performance	2	0.511	6.625	[0.378, 0.624]	0.000 ***			
Business model innovation	10	0.560	8.309	[0.449, 0.654]	0.000 ***			

Note: K = number of studies; r = The corrected total correlation coefficient; Z = Z statistics; 95% CI = 95% confidence interval; Q = test for heterogeneity; df = degrees of freedom. ** $p < 0.01$; *** $p < 0.001$.

4. Discussion

4.1. Discussion of Results

This study analyzed the impact of big data capabilities on the development of enterprises through a meta-analysis approach, while this paper verified the strength of the relationship between big data capabilities and enterprises arising from antecedent, mediating, and consequent variables. This meta-analysis aims to test the feasibility of big data capabilities on the multidimensional development of firms. The results of the study may help to demonstrate the link between big data capabilities and firms. It has been widely recognized that big data can have many transformative impacts on businesses [32–36]. The following is a discussion of the results of the moderating variables between big data capabilities and businesses. The medium-strength positive correlation (r = 0.486) between big data capabilities and enterprises confirms its strategic significance, aligning with the

resource-based view—which posits that valuable, rare resources (like big data capability) drive competitive advantage. This finding resolves inconsistencies in previous studies (e.g., some reporting strong effects, others weak) by synthesizing a larger sample, demonstrating that big data capability is not merely a technological tool but a core asset for value creation.

4.1.1. Antecedent Variable Effect

Antecedent variables such as learning orientation, executive support, environmental dynamics, strategic orientation and others can contribute to big data capability, with learning orientation and executive support and big data capability having a greater positive effect on the firm. Antecedent variables such as corporate culture and organizational structure affect the extent of adoption and application of big data in a firm. Based on the results of the meta-analysis of big data capabilities and enterprises, antecedent variables such as executive support and organizational orientation are effective in using big data capabilities to drive enterprise development activities, but the degree of influence is inconsistent. Learning orientation and executive support play an important role in building big data capabilities [37]. Organizations need to create a culture that encourages learning and innovation, while executive buy-in and support for big data technologies are key to driving the development of big data capabilities [15,38–40]. Enterprises can encourage employees to continue learning and innovating by establishing learning organizations, while executives should actively participate in the development and implementation of big data strategies [41] to provide strong support for the development of big data capabilities [42–44]. Antecedent variables significantly moderate the relationship, with learning orientation ($r = 0.883$) being the strongest driver. This supports the dynamic capability theory: organizations that continuously learn (a dynamic capability) are better at absorbing and applying big data technologies [15,38]. Strategic orientation ($r = 0.676$) and environmental dynamism ($r = 0.677$) also play key roles, indicating that big data capability development must align with corporate strategy and adapt to external changes—echoing Mikalef's argument that contextual factors shape big data effectiveness [17].

4.1.2. Mediation Variable Effect

Mediating variables are not significantly relevant to the big data capabilities of enterprises. Mediating variables such as innovation, supply chain elasticity, knowledge integration, and organizational learning can all have a significant effect on big data capabilities [45–48]. However, the relationship between resource integration and organizational agility on firms' big data capability is not significant. Although mediating variables such as innovation, supply chain resilience, knowledge integration, and organizational learning have a significant effect on big data capability, resource integration and organizational agility do not have a significant effect on big data capability [49–52]. Mediating variables such as innovation, organizational learning, and knowledge integration, on the other hand, influence how effectively companies use big data to create value [53–55]. These findings provide important guidance for firms to optimize their big data strategies, which suggests that firms need to focus on innovation, supply chain, and knowledge management when developing big data capabilities [56–59], while resource integration and organizational agility may not be the key factors to directly enhance big data capabilities. Enterprises can enhance big data capabilities by establishing innovation mechanisms, optimizing supply chain management, strengthening knowledge integration, and organizational learning [53,60–67]. Meanwhile, for the enhancement of resource integration and organizational agility, it is necessary to combine the actual situation of the enterprise to find suitable paths and methods [68–74]. The non-significant overall effect of mediating variables contrasts with significant individual correlations (e.g., organizational agility: $r = 0.631$). This

discrepancy may arise because mediating mechanisms are context-specific; for example, innovation and knowledge integration are effective in technology-intensive industries but less so in traditional sectors. Resource integration shows no significant effect, possibly because excessive resource aggregation may hinder flexibility—suggesting that enterprises should prioritize "smart integration" over blind accumulation.

4.1.3. Outcome Variable Effect

The effect of outcome variables on the relationship between big data capabilities and enterprise is more significant. Big data capability can effectively regulate enterprise business model innovation [75–80], enterprise performance [34,35,81–83], and help promote sustainable development and innovation. When pursuing big data capabilities, enterprises need to clarify the positive relationship between big data capabilities and enterprise performance. This means that organizations should not only view big data as a technological tool but also as a strategic resource [84,85] that can drive business development and innovation [86]. Enterprises should actively invest in the research and development and application of big data technologies [85] to optimize business processes and enhance market competitiveness through data-driven decision-making [87]. At the same time, enterprises also need to pay attention to the integration of big data and business to ensure that the implementation of technology can fit with the strategic objectives of the enterprise [88,89]. Outcome variables highlight the practical value of big data capability, with enterprise innovation performance (r = 0.730) and business model innovation (r = 0.560) as key outputs. This aligns with Oesterreich [88], who emphasized that big data's value lies in transforming business logic, not just optimizing processes. The weak correlation with group control relationships (r = 0.220) suggests that big data capability is less effective in rigidly controlled organizations, emphasizing the need for flexible governance.

Big data capabilities not only directly affect the performance of an organization but also modulate its business model innovation [90,91]. This means that when enterprises use big data, they should not only focus on data collection and analysis but also combine big data capabilities with their business models to promote innovation and sustainable development. Enterprises can optimize their business models and enhance their competitiveness by using big data technologies [32,92,93]. At the same time, enterprises should also take big data capabilities as an important driving force for innovation and development, and achieve sustainable development through data-driven innovation [94].

4.2. Significance

Through meta-analyses, we clarify the positive relationship between big data capabilities and enterprises and delve into the moderating variables that affect this relationship. These findings provide an important basis for enterprises to strengthen their big data capabilities and optimize their big data strategies. From the discussion of the results, we can see that although the impact of big data capabilities on enterprises varies in many aspects, overall, big data capabilities have a positive impact on the development of enterprises and are an effective way to promote enterprise performance improvement [93]. This study can provide feasible references for further exploring how to maximize the value of big data capabilities in different industries and scenarios, and how to cope with the challenges and risks brought by big data.

In theoretical significance, this study advances the literature as follows: (1) Quantifying the overall effect of big data capability on enterprises, filling the gap of fragmented evidence; (2) Identifying boundary conditions through moderator analysis, enriching the theoretical framework of "big data capability-enterprise performance" with antecedent and outcome

variables; (3) Bridging the resource-based view and dynamic capability theory, explaining how static resources (data) and dynamic capabilities (learning, agility) interact to create value.

In practical significance, for managers, the findings provide actionable strategies:

(1) Cultivate antecedents: Prioritize building a learning-oriented culture and aligning strategic goals with big data initiatives; for example, allocate resources to employee training on data analytics and integrate big data into long-term strategic planning.
(2) Optimize mediating mechanisms: Focus on organizational agility and knowledge integration to translate big data capability into outcomes. For instance, establish cross-departmental data-sharing platforms to enhance knowledge flow.
(3) Target outcomes: Prioritize innovation performance and business model innovation; for example, use customer behavior data to develop new products or adopt data-driven pricing models.

4.3. Limitations and Future Directions

Although the meta-analysis methods and research evidence used in this paper have their merits, they also have several limitations. Despite its contributions, this study has limitations:

Publication bias and data dependence: While tests (Egger's $p = 0.284$; fail-safe N = 1807) suggest no significant publication bias, the reliance on published studies may exclude non-significant results. Additionally, the meta-analysis is based on correlational data, limiting causal inferences—future longitudinal studies are needed to verify causality.

Sample and language bias: Most included studies are from Asian contexts (especially Chinese), and over 30% of references are master's theses (with lower academic rigor), potentially reducing generalizability. Future research should include more studies from Western and emerging economies, and prioritize peer-reviewed journals.

Heterogeneity and variable coverage: Although subgroup analysis addressed heterogeneity ($I^2 = 93.5\%$), unobserved factors (e.g., industry type) may still affect results. Some variables (e.g., "other" antecedents/mediators) were grouped due to small sample sizes, limiting depth—expanding the sample to include more variables is needed.

Future research directions: (1) Explore causal mechanisms using experimental or longitudinal designs; (2) Examine industry-specific differences (e.g., manufacturing vs. service); (3) Investigate how digital leadership or policy support moderate the relationship between big data capabilities and enterprises.

5. Conclusions

The results of the analyses of this study show that big data capabilities play an increasingly important role in enterprise operations and development. This study systematically explores the relationship between big data capabilities and enterprise development through meta-analysis, with the following key conclusions:

First, big data capability has a significant positive medium-strength correlation with enterprise outcomes (r = 0.486), confirming its strategic value as a core asset for enterprises. This finding integrates fragmented empirical evidence, resolving inconsistencies in previous studies and providing robust support for the argument that "big data capability drives enterprise value creation." Second, the moderating effect analysis reveals clear boundary conditions: Antecedent variables (learning orientation, strategic orientation, etc.), play a critical role in enhancing the impact of big data capability, among which learning orientation stands out as the most impactful driver—highlighting that enterprises prioritizing a culture of continuous learning are more likely to leverage big data for development; Outcome variables (enterprise innovation performance, business model innovation, etc.), directly reflect the practical value of big data capability, with enterprise innovation performance

showing the strongest correlation, indicating that big data capability is particularly effective in promoting innovation. In contrast, mediating variables have an overall non-significant effect, suggesting that their role may be context-dependent and requires further exploration. Theoretically, this study enriches the dynamic capability theory and resource-based view by empirically verifying that big data capability, as a dynamic resource, interacts with organizational antecedents to create value. Practically, it provides actionable guidance: enterprises should cultivate a learning-oriented culture and align strategic orientation with big data development; focus on translating big data capability into innovation performance through mechanisms like organizational agility and knowledge integration; and avoid over-reliance on resource integration, which shows limited mediating effects.

From a broader perspective, as digital transformation accelerates, the relationship between big data capabilities and enterprises will become more complex. Future research should go beyond correlation analysis to explore causal mechanisms through longitudinal studies, and expand sample diversity to enhance global generalizability.

Author Contributions: Methodology, Y.X.; Software, Q.C.; Validation, Y.N.; Formal analysis, L.F.; Data curation, Q.C. and Y.N.; Writing—original draft, Q.C.; Writing—review and editing, Y.X. and J.L.; Visualization, L.F.; Project administration, J.L.; Funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China grant number 42330108 and National Natural Science Foundation of China grant number 42361069.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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

Appendix A

Web of science search equation:

(TS = (Big Data Capability OR Capability, Big Data OR Big Data, Capability OR Big Data, Analysis OR Analysis, Big Data OR Analysis, Big Data OR Big Data, Management OR Management, Big Data OR Big Data, Adoptions OR Adoptions, Big Data OR Big Data Analysis OR Big Data Management OR Big Data Adoption OR Big Data))

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