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Exploration of the Impact of Policy Empowerment and Digital Transformation on the Advancement of Enterprise Human Capital Structure

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Abstract: This study examines how enterprise digital transformation influences human capital structure advancement within China's government-driven big data initiative. Using the 2016 National Big Data Comprehensive Experimental Zone as a quasi-natural experiment, data from 2011 to 2022 are analyzed through the Difference-in-Differences (DID) and Panel Vector Autoregressive (PVAR) models. Findings indicate that national big data policies enhance human capital structure by boosting corporate innovation. Digital transformation further optimizes human capital, with both factors reinforcing each other. The experimental zone policy accelerates this process through innovation. This study underscores digital transformation as a key driver of enterprise human capital upgrading.

Keywords: National Big Data Comprehensive Experimental Zone; digital transformation; human capital structure; entropy weight method; difference-in-differences model; PVAR model

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1. Introduction

In the digital economy era, digital transformation drives high-quality economic development. China's policies, such as the "14th Five-Year Plan for Digital Economy Development" promote digital-real economy integration and a data-driven landscape. Emerging technologies like big data reshape business models and impact enterprise human capital structures. This study uses the National Big Data Comprehensive Experimental Zone as a quasi-natural experiment to explore the link between digital transformation and human capital structure.

2. Research Hypotheses

To systematically explore the relationship between policy empowerment, enterprise digital transformation, and human capital structure, this study proposes the following hypotheses:

1) The establishment of the big data comprehensive zone can directly promote the improvement of enterprise innovation capabilities.
2) There exists a dynamic interaction effect between policy empowerment, enterprise digital transformation, and human capital structure.

These hypotheses aim to clarify the complex interactions between policy empowerment, digital transformation, and human capital structure, as well as their impact on enterprise innovation, with a particular focus on the unique dynamics of enterprise development in the context of the digital economy. This study will contribute to a deeper understanding of how these variables interact, thereby driving sustainable development and innovation in enterprises [1].

3. Research Methods

3.1. Variable Selection and Data Sources

3.1.1. Variable Selection for Difference-in-Differences Model

- Dependent Variable

The proportion of intangible assets in a company (Wmpg5) reflects the company's innovation capabilities. Intangible assets include patents, brands, goodwill, technology, employee skills, and organizational processes, which are key resources for research and innovation. This study adopts the approach to use this as a measure of innovation capability [2].

- Independent Variable

The independent variable (dep) indicates whether the listed company is located in a region approved for the creation of a National Big Data Comprehensive Experimental Zone. If the pilot program was approved in 2016, the year and subsequent years are marked as 1; otherwise, they are marked as 0. Given that the influence of the Pearl River Delta Experimental Zone extends to other cities within Guangdong Province, this study treats all cities in Guangdong as the treatment group.

- Control Variables

To reduce the impact of omitted variables, this study includes the following control variables: company size (cs), debt-to-equity ratio (alt), the size of independent directors (sid), total asset growth rate (tagr), duality of roles (dua), and audit opinion (ao).

3.1.2. Variable Selection for PVAR Model

- Policy Dummy Variable for National Big Data Comprehensive Experimental Zone

This study introduces enterprise innovation capability (measured by the proportion of intangible assets) as an exogenous shock to policy changes, aiming to explore the causal relationship between national big data policies, enterprise digital transformation, and enterprise human capital structure, as well as the dynamic responses of variables to these shocks.

- Enterprise Digital Transformation

This research uses Python's Jieba library to analyze the annual reports of publicly listed companies. The keywords are grouped into five categories: artificial intelligence, blockchain, cloud computing, big data, and digital technologies. Their frequencies are calculated using word frequency statistics. The entropy weight method then determines the weights of these indicators based on keyword frequencies, as shown in the Table 1 below.

Table 1. Indicator Information Based on the Entropy Weight Method.

Indicator	Indicator Definition	Indicator Direction	Indicator Weight
Artificial Intelligence Technology	This study calculates the total word frequency, covering AI, Business Intelligence, Image Understanding, Decision Support Systems, Intelligent Data Analysis, Intelligent Robots, and Machine Learning. It also includes Deep Learning, Semantic Search, Biometric	positive	0.14465442

	Recognition, Identity Verification, Autonomous Driving, and Natural Language Processing.		
Big Data Technology	The total word frequency listed in parentheses encompasses concepts like Big Data, Data Mining, Text Mining, and Data Visualization. It also covers Heterogeneous Data, Credit Reporting, and technologies such as Augmented Reality, Mixed Reality, and Virtual Reality.	positive	0.1562654
Cloud Computing Technology	The aggregated word frequency in parentheses encompasses concepts like Cloud Computing, Stream Computing, Graph Computing, and Memory Computing. It also includes Secure Multi-party Computing, Brain-inspired Computing, Green Computing, and Cognitive Computing, along with Converged Architecture, Large-scale Concurrency, EB-level Storage, the Internet of Things, and Cyber-Physical Systems.	positive	0.1512393
Blockchain Technology	The word frequency in parentheses covers terms like Blockchain, Digital Currency, Distributed Computing, Differential Privacy Technology, and Smart Financial Contracts.	positive	0.4282263
Digital Technology Application	The total word frequency in the parentheses includes terms such as Mobile Internet, Industrial Internet, E-commerce, Mobile Payments, Smart Energy, IoT, Smart Agriculture, Smart Healthcare, Smart Homes, Smart Investment Advisors, Digital Marketing, Unmanned Retail, Internet Finance, Fintech, Quantitative Finance, and Open Banking.	positive	0.1196147

- Proxy Variable for Enterprise Human Capital Structure

The proportion of technical staff is an important indicator for measuring the advancement of enterprise human capital structure, reflecting the ratio of high-skilled employees and their role in driving technological innovation and competitiveness. This study uses it as a proxy variable for enterprise human capital structure [3].

3.1.3. Variable Types and Definitions

Table 2 presents the descriptive statistics for each variable.

Table 2. Descriptive Statistics for Each Variable.

Variable Name	Variable Symbol	Variable Definition and Description
National Big Data Comprehensive Experimental Zone Policy	dep	The interaction term of the pilot region policy dummy variable and the time dummy variable, with values of 0 or 1
Corporate Innovation Capability	Wmpg5	Proportion of Intangible Assets
Enterprise Digital Transformation	Score	Degree of Digital Transformation, with values as the logarithm of the entropy weight score plus 1

Advancement of Human Capital Structure	ehcs	Proportion of Technical Staff
Company Size	cs	Natural Logarithm of Total Assets for the Year
Debt-to-Equity Ratio	alt	Total Liabilities at Year-End / Total Assets at Year-End
Size of Independent Directors	sid	Number of Independent Directors/Total Number of Directors
Total Asset Growth Rate	tagr	Net Profit / Average Total Assets
Dual Role Integration	dua	If the Chairman and CEO are the same person, the value is 1, otherwise 0
Age of the Enterprise	age	Years since the Company's Listing
Audit Opinion	ao	If the company is audited by the Big Four, the value is 1, otherwise 0

3.1.4. Data Sources and Processing

The data used in this study are sourced from the Wind database, CSMAR database, annual reports of listed companies, and publicly available statistical reports. The research sample consists of Chinese listed companies from 2011 to 2022, excluding delisted companies. Outliers were winsorized, and missing values were partially imputed using interpolation methods. The final sample includes 1,735 companies with a total of 20,820 observations.

3.2. Model Specification

3.2.1. Difference-in-Differences (DID) Model

To accurately measure the "net" policy effect of the Big Data Experimental Zone policy on corporate innovation capability, the Difference-in-Differences (DID) method is applied for quantitative analysis. Dummy variables are set as follows: treat (equals 1 for the treatment group, 0 for the control group) and time (equals 1 after policy implementation, 0 before policy implementation). The interaction term, Dep, represents the interaction between time and treat. Based on this, the DID regression model is specified as follows:

$$Y_{ict} = \alpha_0 + \alpha_1 dep + \alpha_2 contral + u_t + u_v + \varepsilon_{it}$$

In the model, *i* and *t* represent the enterprise and year, respectively. control refers to the control variables, and Y denotes enterprise innovation capability (measured by the proportion of intangible assets).

u_t and u_v represent year and regional fixed effects, respectively, while ε_{it} varepsilonε is the random disturbance term affecting enterprise innovation capability.

3.2.2. PVAR Model

This study uses data from listed companies to develop a Panel Vector Autoregression (PVAR) model, analyzing the dynamic interaction between enterprise digital transformation and human capital structure influenced by the national big data policy [4]. The model employs the degree of digital transformation (Score) and the proportion of technical staff (ehcs) as key variables. Building on insights from the previous Difference-in-Differences (DID) model, it incorporates enterprise innovation capability (proxied by the proportion of intangible assets) to capture policy impacts within the PVAR model. The model's basic structure is as follows:

$$Y_{i,t} = \alpha_0 + \sum_{j=1}^{k} \alpha_j Y_{i,t-j} + \eta_i + \varphi_t + \varepsilon_{i,t}$$

In the model, i represents the individual, and t represents time. $Y_{i,t}$ is an $m \times 1$ times $m \times 1$ vector of observable random variables; α_0 is the vector of intercept terms;

α_j is the $m \times m$ times $m \times m$ coefficient matrix of lagged variables; $Y_{i,t-j}$ represents the j-th order lag of endogenous variables; η_i denotes the individual fixed effect; φ_t represents the time effect; and $\varepsilon_{i,t}$ is the random disturbance term.

In this model, enterprise innovation capability, digital transformation, and human capital advancement are treated as three observable random variables (m = 3), enabling mutual causal interactions between them. The model explores the dynamic relationships through Granger causality tests, impulse response analysis, and forecast variance decomposition. To reduce estimation bias in the coefficient matrix, forward mean differencing and within-group mean differencing methods are used to eliminate individual and time effects.

4. Results

4.1. Difference-in-Differences (DID) Model

4.1.1. DID Regression Results

The DID model is employed to assess how the Big Data Experimental Zone influences enterprise innovation capability. The results indicate that the coefficient of the policy interaction term (dep) is 0.00187 with a p-value less than 0.01, suggesting a statistically significant positive association (Table 3). This effect may be attributed to the policy's role in fostering research collaboration, technology transfer, and talent development, as well as reducing innovation costs and stimulating market demand through economic support and public procurement.

Table 3. DID Regression Results.

VARIABLES	wmpg5	VARIABLES	wmpg5
dep	0.00187*** (0.000414)	ao	0.000595 (0.000901)
cs	-0.00120*** (0.000397)	age	-0.000415*** (0.000153)
alt	-0.00234* (0.00141)	tagr	-0.0109*** (0.00119)
sid	-0.00000397 (0.0000320)	Observations	20,647
dua	-0.000189 (0.000389)	R-squared	0.711

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

However, firm size and total asset growth rate exhibit a negative correlation with innovation capability, possibly due to increased decision-making complexity and risk aversion in larger enterprises, which may hinder disruptive innovation investment.

4.1.2. Parallel Trend Assumption Test

The application of the Difference-in-Differences (DID) method requires the parallel trend assumption to hold, meaning that before policy implementation, the difference in enterprise innovation capability between the treatment and control groups should be minimal. If this assumption is violated, the observed differences may stem from inherent factors of the treatment group rather than the policy intervention. The specific formula is as follows:

$$\boldsymbol{Y_{it}} = \alpha_0 + \sum_{\boldsymbol{i=-5}}^{\boldsymbol{6}} \alpha_{\boldsymbol{it}} \boldsymbol{D_{it}} + \sum \boldsymbol{\alpha_4 Z_{it}} + \boldsymbol{\mu_t} + \mathbf{i} + \varepsilon_{it}$$

In the equation, t represents the policy implementation year, with $t = 0$ indicating the implementation year, $t < 0$ the pre-policy period, and $t > 0$ the post-policy period. $\boldsymbol{D_{it}}$ represents the estimated policy effect. As shown in Figure 1, the parallel trend assumption holds, as both groups exhibit similar trends before the policy. Post-implementation, innovation capability increases, particularly during the post-3 to post-6 period, indicating a significant positive impact of the Big Data Experimental Zone policy. This may result from improved resource utilization and enhanced knowledge sharing through network and synergy effects. Despite some fluctuations, the overall upward trend confirms the policy's effectiveness in fostering innovation.

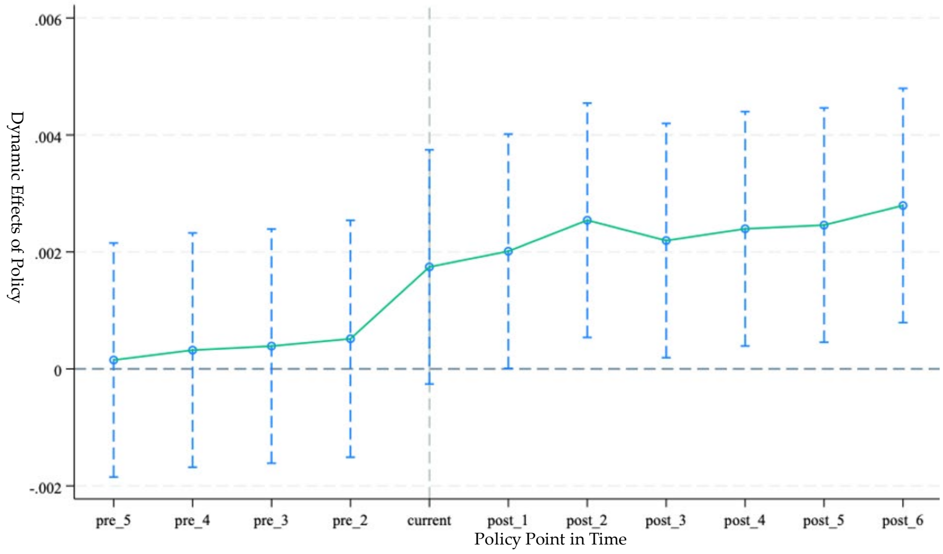

Figure 1. Parallel Trend Test Chart.

- Individual Placebo Test

The individual placebo test examines whether the policy effect is due to random fluctuations by repeating the analysis under a no-policy scenario. As shown in Figure 2, most *p*-values exceed 0.05, indicating that the effect is insignificant without policy intervention, confirming that the observed policy effect is not coincidental. The kernel density curve is concentrated around zero and evenly distributed, with no systematic bias, verifying the reliability of the model and policy effect estimation.

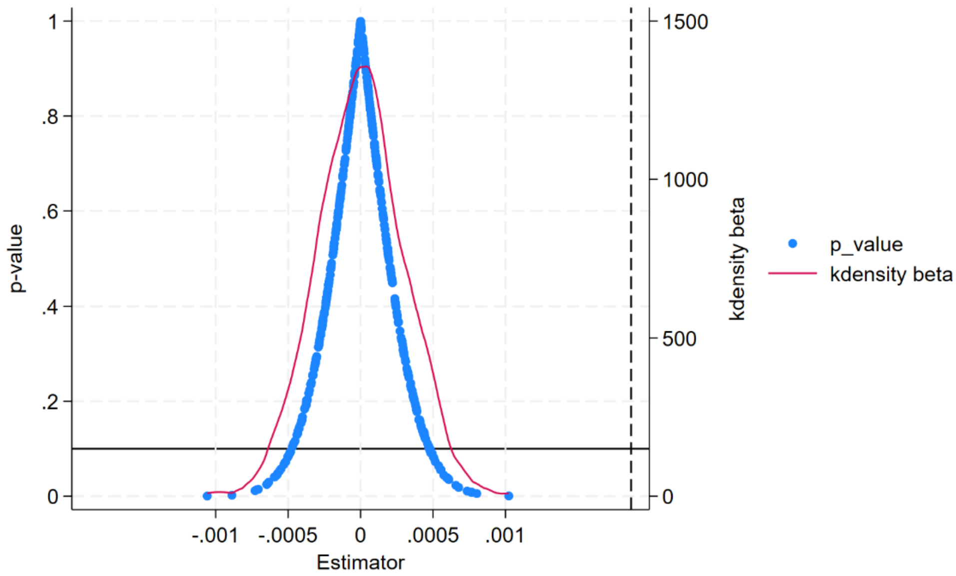

Figure 2. Individual Placebo Test Results.

- Time Placebo Test

This study employs a time placebo test to validate the robustness of the Big Data Experimental Zone policy's impact on enterprise innovation capability. The test alters the policy implementation timeline to examine whether the model effect remains significant, eliminating potential biases from model characteristics or external factors. The results indicate that when the policy is assumed to take effect one year earlier, the *p*-value is 0.111 (Table 4), exceeding the conventional significance threshold of 0.1, suggesting an insignificant effect in the absence of the actual policy intervention. This supports the hypothesis that the observed improvement in enterprise innovation capability is directly attributable to the policy rather than external factors.

Table 4. Time Placebo Test Results.

wmpg5	Coefficient	Std. err.	*t*	*p* > |t|	95% conf.	interval
dep_1	0.000000229	0.000000144	1.59	0.111	0.0000000525	0.000000511
cs	0.0009592	0.0002611	-3.67	0	0.001471	0.0004474
alt	0.0020185	0.0011507	-1.75	0.079	0.004274	0.000237
sid	0.00000569	0.0000302	0.19	0.851	0.0000535	0.0000649
tagr	0.0113073	0.0010562	10.71	0	0.0133776	0.009237
dua	0.0002434	0.0003661	-0.66	0.506	0.0009609	0.0004741
age	0.0004329	0.0001076	-4.02	0	0.0006438	0.0002219
ao	0.0006797	0.000793	0.86	0.391	0.0008746	0.0022341
cons	0.0732038	0.0063013	11.62	0	0.0608526	0.0855549
sigma_u	0.02250763					
sigma_e	0.01479091					
rho	0.69839842					

4.2. PVAR Model

4.2.1. Variable Substitution

Since the policy dummy variable (0-1) cannot be applied in the PVAR model, and the DID model indicates that the Big Data Experimental Zone policy significantly impacts enterprise innovation capability, this study introduces enterprise innovation capability as a proxy to capture the effect of policy changes.

4.2.2. Stationarity Test

To ensure the accuracy of model estimation and prevent spurious regression, this study employs five methods to conduct stationarity tests on the variables: the LLC test, IPS test, HT test, ADF-Fisher test, and PP-Fisher test [5]. The test results are presented in Table 5.

Table 5. Stationarity Test Results.

Variable	IPS Test	LLC Test	HT Test	ADF-Fisher Test	PP-Fisher Test	Test Conclusion
Wmpg10	-26.3479***	-150***	0.3961***	7837.6475***	7837.6475***	Stationary
Wmpg20	-11.0469***	-120***	0.3041***	5131.5689***	5131.5689***	Stationary
Wmpg30	-33.7723***	-95.4078***	0.2592***	10,600***	10,600***	Stationary

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively. The numbers in the table represent the corresponding test statistics from the IPS test, HT test, LLC test, ADF-Fisher test, and PP-Fisher test, with all values rounded to three decimal places.

The test results indicate that the variables Wmpg10, Wmpg20, and Wmpg3 in the model have all passed the stationarity test, rejecting the null hypothesis of the presence of a unit root. This suggests that the data for enterprise innovation capability, enterprise digital transformation, and the advancement of human capital structure are stationary, making it feasible to establish the PVAR model.

4.2.3. Determination of Optimal Lag Order

This study determines the optimal lag order of the PVAR model using the Consistent Model Selection Criterion (CMMSC). The results are presented in Table 6.

Table 6. Lag Order Selection.

lag	CD	J	J *p*-value	MBIC	MAIC	MQIC
1	0.9965561	84.54695	0.0000000759	-169.3792*	30.54695	-36.47821
2	0.9964327	27.60857	0.0682672	-141.6755	-8.391433*	-53.07487*
3	0.9967647	20.89937	0.0131048	63.74269	2.899367	19.44235

Note: * indicates the optimal lag order selected based on the MBIC, MAIC, and MQIC criteria.

Table 6 shows that the optimal lag order determined by MBIC is 1, while MAIC and MQIC suggest an optimal lag order of 2. Therefore, this study sets the lag order of the PVAR model to 2.

4.2.4. Granger Causality Test

This study conducts a Granger causality test on the three variables—enterprise innovation capability, enterprise digital transformation, and the advancement of human capital structure. The results are presented in Table 7.

Table 7. Granger Causality Test Results.

	Chi-square Value	Degrees of Freedom	*p*-value
Enterprise digital transformation is not the Granger cause of enterprise innovation capability.	5.218	2	0.007
The advancement of human capital structure is not the Granger cause of enterprise innovation capability.	7.313	2	0.013
Enterprise innovation capability is not the Granger cause of enterprise digital transformation.	12.367	2	0.005
The advancement of human capital structure is not the Granger cause of enterprise digital transformation.	10.994	2	0.021
Enterprise innovation capability is not the Granger cause of the advancement of human capital structure.	2.966	2	0.059
Enterprise digital transformation is not the Granger cause of the advancement of human capital structure.	21.999	2	0.000

Table 7 shows that enterprise innovation capability significantly influences digital transformation, indicating that changes in innovation capability driven by policy changes can predict variations in digital transformation. Digital transformation has a significant impact on the human capital structure, serving as a key predictor of its changes. Additionally, the human capital structure significantly affects innovation capability, suggesting that its adjustments feedback into policy formulation.

These findings reveal the interactive relationship between policy, digital transformation, and human capital structure. Policy indirectly affects the human capital structure through digital transformation, while adjustments in human capital feedback into policy decisions. This underscores the need for policymakers to consider the long-term implications when promoting digital transformation and human capital upgrading.

To further clarify the short-term and long-term causal relationships among the three variables, GMM estimation and impulse response analysis are required.

4.2.5. GMM Coefficient Estimation

The system GMM estimation results based on the optimal lag order of 2 are presented in Table 8.

Table 8. GMM Coefficient Estimation Results.

	Enterprise Innovation Capability		Enterprise Digital Transformation		Advancement of Human Capital Structure	
L1_Wmpg10	0.8121937	0	-0.0107445	0.017	-1.119073	0.02
L2_Wmpg10	0.025298	0.02	0.0030158	0.103	0.038718	0.851
L1_Wmpg20	0.2192112	0.01	0.7285541	0	8.332558	0
L2_Wmpg20	-0.0504161	0.418	0.0987647	0	0.8556775	0.485
L1_Wmpg30	-0.0047532	0.04	-0.0007197	0.114	0.6790759	0
L2_Wmpg30	-0.0002632	0.726	0.0003734	0.009	0.0553204	0.001

In the enterprise innovation capability equation, the coefficient of the first lag of innovation capability is significantly positive, indicating a positive impact on current innovation capability. However, the first lag of enterprise digital transformation is not significant, possibly due to the high uncertainty and risk associated with digital transformation, which may lead enterprises to adopt risk-averse strategies and reduce investments in high-risk innovation projects.

In the enterprise digital transformation equation, the coefficients of the first and second lags of digital transformation are positive, indicating its continuous driving effect on current transformation. However, the negative coefficient of the second lag of human capital advancement suggests a possible mismatch between the demand for new skills driven by digital transformation and the existing labor market supply, leading to short-term inefficiencies or shortages in human capital.

In the human capital advancement equation, the coefficients of the first lag of digital transformation and both the first and second lags of human capital advancement are positive, suggesting that in the short term, human capital advancement facilitates enterprise digital transformation. This implies that policy, digital transformation, and human capital structure interact across different time scales. Notably, digital transformation has a significant long-term impact on human capital advancement, highlighting the importance of strategic planning for enterprise development.

4.2.6. Unit Root Test

The next step is to conduct a stability test for the PVAR model by calculating the unit root eigenvalues to determine whether they all lie within the unit circle, thereby verifying the model's stability.

Figure 3 illustrates that all six estimated points of the PVAR model lie within the unit circle, confirming the model's stability and the presence of a long-term stable relationship among the variables.

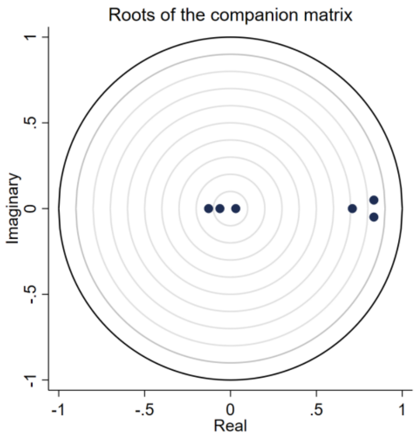

Figure 3. Unit Root Test Results.

4.2.7. Impulse Response

The GMM estimation of the PVAR model reveals the dynamic relationships among variables [6,7]. To further clarify these relationships, this study conducts an impulse response analysis to simulate the dynamic response paths to standardized shocks among the variables.

The horizontal axis represents time, and the vertical axis shows the shock magnitude. The shaded area between the two outer lines denotes the 5% confidence interval, based on Monte Carlo simulations with two standard errors, while the red line in the center represents the impulse response function curve [8].

The impulse response results in Figure 4 show that in subplot 2, when the government-driven big data initiative experiences a one standard deviation shock, enterprise digital transformation is initially slightly negatively affected by enterprise innovation capability but stabilizes over time, reaching its peak in the fourth period before gradually increasing. This finding aligns with previous results.

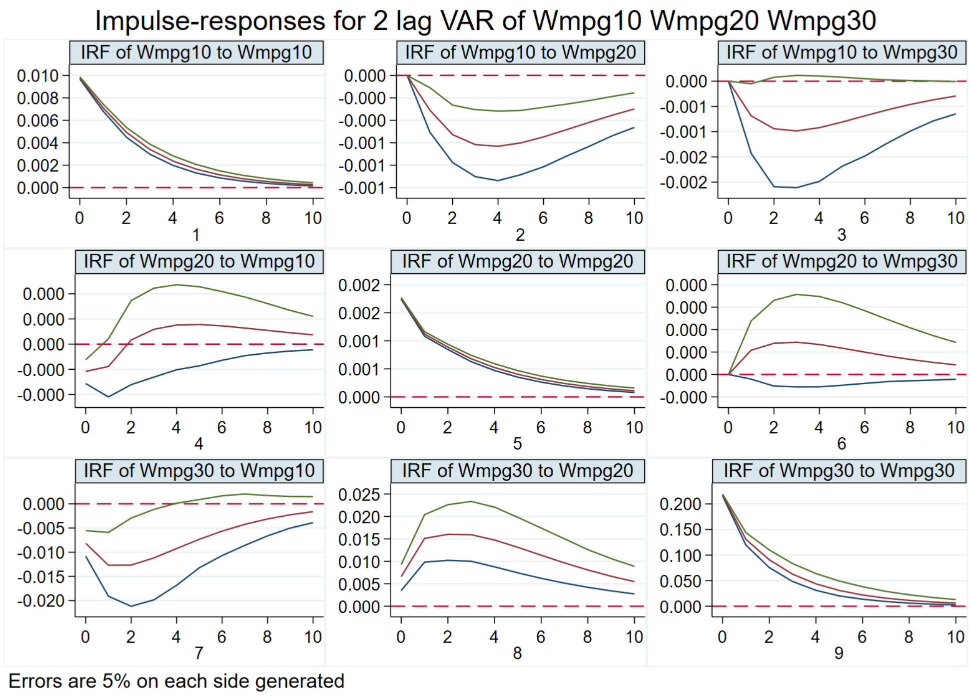

Figure 4. Impulse Response Results.

Subplots 4 and 6 indicate that a one standard deviation shock to enterprise digital transformation initially negatively affects innovation capability in the first period but turns positive from the third period onward and persists until the tenth period. This suggests that the positive effect of digital transformation on enterprise innovation capability takes time to manifest and is sustained [9]. Additionally, human capital advancement exhibits a long-term positive impact following a digital transformation shock, indicating that digital transformation drives the advancement of human capital structure over the long term.

Subplots 7, 8, and 9 show that a shock to human capital advancement leads to an immediate positive response in enterprise digital transformation, peaking in the second period and gradually declining, but with a weak positive effect persisting until the tenth period. The self-impact of human capital advancement shows a significant positive effect that strengthens over time, highlighting its self-reinforcing nature [10].

These impulse response figures reveal the complex interactions and time-lag effects among policy, enterprise digital transformation, and human capital structure. policy changes significantly impact enterprise innovation capability and internal transformations such as digitalization, with sustained effects and evolving trends. Notably, digital transformation exerts a long-term positive influence on human capital advancement, emphasizing the need for enterprises to incorporate these dynamics into strategic planning to enhance sustainable growth and competitive advantage.

4.2.8. Variance Decomposition

The variance decomposition results measure the contribution of different shocks to the fluctuations of endogenous variables, providing an accurate assessment of the interactions among enterprise innovation capability, digital transformation, and human capital advancement. In the impulse response analysis, the analysis period is set to 10 periods, and the variance decomposition results are presented in Table 9.

Table 9. Variance Decomposition Results.

Variable	Shock Variable		
	Wmpg10	Wmpg20	Wmpg30
Wmpg10	1	0	0
	0.9926971	0.0009023	0.0064006
	0.9800392	0.0034124	0.0165484
	0.9659611	0.0071635	0.0268753
	0.9526305	0.0117486	0.0356209
	0.9409932	0.0167567	0.0422501
	0.9312901	0.0218402	0.0468696
	0.9234144	0.0267335	0.049852
	0.9171199	0.0312548	0.0516253
	0.9121316	0.0352964	0.052572
Wmpg20	0.0007646	0.9992355	0
	0.004059	0.990913	0.005028
	0.0062125	0.9762669	0.0175206
	0.0077665	0.9602124	0.0320211
	0.0087857	0.9448469	0.0463674
	0.0094006	0.9312917	0.0593076
	0.0097318	0.9199069	0.0703613
	0.009879	0.9106649	0.079456
	0.0099169	0.9033514	0.0867317
	0.0098972	0.89768	0.0924228

Wmpg30	0.0048637	1.29E-06	0.9951349
	0.0101313	0.003057	0.9868116
	0.0162569	0.0071604	0.9765826
	0.0224596	0.0123346	0.9652058
	0.0282482	0.0179364	0.9538153
	0.0333316	0.0235174	0.9431511
	0.0375935	0.0287494	0.9336571
	0.0410389	0.0334359	0.9255252
	0.0596303	0.038074	0.9022957
	0.0620035	0.0415949	0.8964016

In the initial phase, the policy mainly influences itself. However, from the second phase onward, the effects of enterprise digital transformation and human capital development gradually become more apparent. By the tenth period, the policy effect stabilizes, with self-influence making up 91.13%, human capital development contributing 5.25%, and digital transformation at 3.52%, indicating that human capital development plays a larger role than digital transformation [11,12].

Enterprise digital transformation is predominantly shaped by its own factors and human capital development. Its self-influence starts at 99.92% in the first period but declines to 89.76% over time. The influence from human capital development begins in the second period, increasing from 0.50% to 9.24%. The effect of innovation capability is relatively small, stabilizing at 0.97% by the seventh period.

Human capital development is mainly driven by itself, decreasing from 99.51% to 89.64%. Contributions from innovation capability and digital transformation rise to 6.20% and 4.15%, respectively, showing a continuous upward trend. This suggests that the influence of digital transformation on human capital development strengthens over time.

These variance decomposition results reveal that, while short-term dynamics are largely driven by the past states of each variable, long-term interactions between policy, digital transformation, and human capital development play a significant role. The interaction between digital transformation and human capital development underscores the need to consider these complex interdependencies when formulating corporate strategies and policies. This analysis offers data-driven insights for more effective policy and strategy development, highlighting the importance of comprehensive long-term planning [13,14].

5. Conclusion and Recommendations

5.1. Conclusion

The findings show that the national big data experimental zone policy significantly enhances enterprise innovation capability and interacts dynamically with digital transformation and human capital advancement. The key conclusions are as follows:

1) The big data policy exogenously impacts enterprise innovation capability, which then drives the advancement of human capital structure, with both lag and reinforcement effects.
2) A significant bidirectional Granger causal relationship exists between digital transformation and human capital advancement. Digital transformation plays a key role in upgrading the human capital structure by increasing the demand for high-skilled labor.
3) The big data policy indirectly promotes both digital transformation and human capital upgrading by strengthening innovation capability.
4) The policy's impact on human capital structure is weaker than its impact on digital transformation, likely because it simultaneously increases the demand for low-skilled labor, resulting in less noticeable adjustments in human capital structure.

5.2. Policy Recommendations

When formulating big data policies, the government should consider their impact on enterprise digital transformation and human capital structure. To achieve the goal of "advancing the human capital structure" policies should empower enterprises by leveraging the leading role of digital transformation to promote a dynamic balance and advancement in human capital structure.

5.3. Recommendations for Enterprise Development

Enterprises should incorporate digital transformation and human capital advancement into their long-term strategies. They should leverage digital tools to optimize human resource management, prioritize the cultivation and recruitment of high-skilled talent, and increase investment in fields such as artificial intelligence and big data to enhance competitiveness.

5.4. Recommendations for Talent Development in Higher Education

Universities should accelerate supply-side reforms in talent cultivation by promoting collaboration among academia, government, and industry to train high-quality digital talent. Emphasis should be placed on integrating theory with practice to bridge the gap between talent capabilities and enterprise needs, ensuring a high degree of alignment between digital skills and industry demands. This will provide enterprises with high-quality technical professionals and facilitate the advancement of human capital structure.

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