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Two-Way Empowerment: The Role of Data Resources in Economic and Human Resource Development

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ABSTRACT: In today's world economic system, data resources have become one of the important tools to promote local economic growth. Using China as an example, this study explores the complex relationship between the degree of data progress and local economic welfare. This paper aims to reveal the role of data resources as a catalyst for economic growth by examining the relationship between data flow efficiency, data infrastructure quality, and economic growth measures. At the same time, the research project uses EViews software to conduct econometric analysis of economic indicators such as GDP growth rate, employment data and per capita GDP to verify the relationship between data development level and economic performance. The final study shows that there is a strong positive correlation between effective management and use of data resources and local economic success, and we find that this correlation is particularly strong in regions with better data infrastructure. These findings provide practical evidence for policymakers, such as businesses or governments, and underscore the need to implement data-focused economic development strategies. The article shows that in order to rapidly develop the digital economy to help improve the economic level, increase and attract talents, etc., it is necessary to establish a sound data infrastructure, as well as improve the efficiency and accuracy of data transmission. These findings provide important insights into how businesses use data resources to make strategic decisions.

KEYWORDS: Two-way empowerment, data assets, economic progress, human capital development, data framework, econometric examination

1. INTRODUCTION

This introduction aims to clarify research objectives and highlight the mutually beneficial ability of data to promote local economic growth and human resource development. The research aims to deepen understanding of the impact of data on economic and human resource growth. By examining the fundamentals, it will provide a holistic perspective for making informed policy and business strategic decisions. And deepen understanding of the impact of data on economic and human resource growth. Through the above research methods, it will provide a holistic perspective for making informed policy and business strategic decisions.

In today's digital economic system, data resources have become an important asset to promote the growth of local economy and human resources, and China has achieved remarkable results in the development of digital economy. Using China as an example, this paper explores the complex links between data resource development and local economic welfare, with welfare policies being one of the priorities in attracting talent. Moreover, we analyze the dual functions of data resources in promoting economic development and human resources development, and discuss the relationship between data flow efficiency, data infrastructure quality and economic growth indicators, and also provide ideas and insights for the development of human resources. By analyzing these interactions, we seek to demonstrate how data resources can stimulate the simultaneous development of economic and human resources.

In order to systematically analyze these complex relationships, we propose multiple hypotheses that are consistent with the objectives of the study. In this study, the relationship between the level of digital economy development and local economic performance is explored. It also explores the dual impact of improved data resources on economic and human resource development. In addition, the relationship between the efficiency of data flow and the level of data infrastructure construction is also studied. The paper provides substantive theoretical insights as well as empirical evidence that can help decision makers make effective use of data resources.

Then, we pay attention to China. In this country, big data is used in various fields. For example, companies or businesses use it to enhance business decisions, and governments use it to improve the efficiency of public services. Through this, local governments and enterprises can accurately understand market trends, predict economic changes, and formulate strategies based on real-time data analysis. However, the maximum capacity of data depends on the effectiveness of data transmission, and the effectiveness of data transmission must be built on a solid data framework. Research on enhancing data mobility through data infrastructure and its impact on economic and human resource development in order to develop effective data-driven policies.

In addition to the above, we also examine the interrelationship between data resources and economic and human resource growth. It analyzes how data resources contribute to local economic development, and how economic growth in turn stimulates the advancement and utilization of data. By examining this cycle of growth, this study provides important theoretical and practical aid for data-driven economic and human resource development models. We are eager to provide vital insights to policymakers and industry leaders.

At the same time, in order to systematically analyze these complex relationships, we propose several hypotheses that are consistent with the research objectives. Hypotheses and tests help research and the reader's understanding.

2. LITERATURE REVIEW

In several previous papers, we learned that they studied the application and impact of digital technology in various fields. One of the earlier studies focused on investigating online talent management systems, using questionnaires and interviews with people involved, including recent graduates and senior managers, and found that while these systems show potential in the current job market, they still need improvement. In another study, the authors analyzed the impact of digital technologies on frameworks such as business models by evaluating existing academic articles and global corporate records. According to the report, while digital transformation is important, achieving good results still depends on the combined use of individuals, processes, technology and data. This study conducted a questionnaire survey and hierarchical regression analysis on 210 enterprises to study the impact of digital capability on business model innovation, and found that there is a correlation between digital capability, resource reallocation and business model innovation. Other studies use data mining technology and random forest algorithm for analysis, and its content plays a guiding role in the improvement of human resource management system. These studies all present guidance and ideas on how to reduce brain drain and enhance the risk prediction of brain flow. These articles also describe how to use digital technology and its impact on human resource management, business model innovation, organizational management and environmental quality improvement, respectively using questionnaire survey method, interview method, literature method, quantitative analysis method and data mining method.

One of the most important paper is the "China Local Data Development Report (2023)" and "Data Development Index (DDI)" released by Tsinghua University, which shows that the degree of data development is directly related to the level of local economic growth. This article is of great significance to my research. The report also highlights the mutual reinforcement between data resources and economic development, as well as the positive correlation between the efficiency of data flow and the degree of data infrastructure development. However, these literatures did not mention the positive correlation between data development level and local economic level, the mutual enabling relationship between data resources and economic development, and the positive correlation between data flow efficiency and data infrastructure construction level. Therefore, I decided to investigate the problem from this particular perspective. While the current literature extensively explores the use of digital technologies in various fields, it often focuses on the local impact of individual technologies or industries and lacks a comprehensive assessment of the overall impact of data resources. For example, many studies have focused on the impact of digitization on company processes and structures, without looking at the impact of survey data development on the overall well-being of the local economy. In addition, these studies are often done using questionnaires that, while capable of providing insights, may lack statistical evidence to confirm the exact relationship between data resources and economic success. While some studies acknowledge the mediating role of information sharing and value creation in service innovation, few studies have examined the impact of data infrastructure maturity on the effectiveness of data flows, and thus macroeconomic growth.

Additional empirical study is required to investigate the specific mechanisms via which data resources can promote local economic growth by improving decision-making and boosting economic activity.

This study aims to address these issues by formulating specific hypotheses and employing rigorous statistical analytic techniques. Its objective is to offer complete theoretical insights and empirical evidence that can assist policy makers in making optimal use of data resources. This paper aims to address the gap in existing literature by examining the correlation between data development indicators and economic performance in various regions. It will offer new insights and evidence on how data resources play a crucial role in fostering both economic and human resource development. This will not only enhance the theoretical framework, but also provide valuable guidance for practice, particularly in policy formulation and corporate strategic decision-making.

3. METHODOLOGY

3.1 Data collection and interpretation

This study includes collecting a wide range of data sets to thoroughly examine the complex relationship between the amount of data development and local economic health. These encompass data development indicators, data accessibility and quality, economic growth indicators (such as GDP growth rate and GDP per capita), employment statistics, and sector-specific economic data. Furthermore, the emphasis was placed on the extent of data infrastructure development and the effectiveness of data transmission during the data collection process. The analysis also incorporated control variables such as the policy environment, geographic region, and demographic data.

The Data Development Index (DDI), a crucial element of our analysis, was published by Tsinghua University in 2023. This index assesses the extent of data advancement in China's 31 provincial-level areas, encompassing factors such as the creative utilization of data, the flow of data components, the establishment of data resources, data infrastructure, data governance, and security. The article immediately cites the results and pertinent studies from the DDI to clarify how they affect local economic statistics.

In order to guarantee the precision and dependability of the data analysis, all data were standardized before conducting statistical analysis to exclude any missing values and outliers. Prior to conducting additional statistical analysis, the data underwent normalization operations using EViews software.

The economic and human resources data, including as GDP growth rates and per capita GDP, for each province are methodically arranged in Appendix Tables 2 and 3. The tables in this study provide the data in a format that enables readers to perform additional investigations and independently verify the conclusions.

The thorough examination of this vast data collection uncovers the intricate relationship between data resources and the growth of both economic and human resources. The statement demonstrates how data resources can serve as accelerators for both economic growth and the development of human resources. These observations highlight the crucial significance of building resilient data infrastructure and improving the efficiency of data flow, providing substantial empirical evidence for policymaking procedures.

This section provides a comprehensive and well-structured explanation of the methodology and data used in the study. It establishes a strong basis for analyzing the results and their consequences in the next sections of your thesis.

Specific data reference and interpretation

The national average for China's Local Data Development Index (DDI) is 0.41, with Beijing scoring the highest at 0.61. In the classification by region type, Beijing and Shanghai lead the 'Leading' category with an average DDI of 0.59. Tianjin and Chongqing are categorised in the 'Breakthrough' tier, averaging 0.43. For the provincial segment, Zhejiang, Shandong, Guangdong, and Jiangsu are also in the 'Leading' tier, while Fujian through Henan fall into the 'Breakthrough' group with the same average. Further, Liaoning to Xinjiang are classified as 'Aggressive' with an average of 0.32, and Ningxia, Qinghai, and Tibet are in the 'Catch-up' category, averaging 0.26.

Table 1 : 2023 DDI IN CHINA (31 Province)

Category	DDI Average	Regions
Leading	0.59	Beijing, Shanghai, Zhejiang,Shandong, Guangdong, Jiangsu
Breakthrough	0.43	Tianjin, Chongqing, Fujian, Guizhou, Sichuan, Hubei, Guangxi, Anhui, Hunan, Hebei, Jiangxi, Hainan, Henan
Enterprising	0.32	Liaoning, Shanxi, Shaanxi, Yunnan, Jilin, Heilongjiang, Gansu, Inner Mongolia, Xinjiang
Aggressive	0.26	Ningxia, Qinghai, Tibet

In addition, we also have to consider issues such as data flow efficiency, which we can learn from the information published by the National Bureau of Statistics and other official websites. From 2018 to 2023, China has made significant progress in strengthening its data infrastructure to support its growing digital economy needs. The expansion of data centres, extensive network coverage and faster Internet speeds, especially the widespread deployment of 5G technology, have significantly improved connectivity in urban and rural areas. This development is essential for facilitating efficient data flows, for modern economic activity and for fostering innovation.

At the same time, China's policy environment has been cleverly structured to support the digital economy. These sectors have seen a surge in public and private investment, supported by a policy environment that includes initiatives such as the 14th Five-Year Plan (which emphasises digital integration across economic sectors). These advances have not only facilitated connectivity and data flows, but also economic sectors such as high-tech and manufacturing, which increasingly rely on sophisticated data analytics for innovation and efficiency. In addition, from a geographical point of view, China presents distinct regional economic characteristics, the Yangtze River Delta, the Pearl River Delta and other coastal areas of economic vitality and scientific and technological progress are leading. In contrast, the central and western regions focus on equitable growth and overcoming development gaps, while the Northeast region faces industrial decline.

Demographically, China faces challenges with an ageing population but also opportunities within its large working-age demographic. Educational attainment, particularly at higher levels, remains a concern, though efforts are underway to bridge this gap as part of broader human resource development. The dynamics of population mobility, highlighted by significant urban migration, underscore the evolving urban landscape, which offers both challenges and opportunities for sustainable development.

Moreover, economic indicators such as GDP growth rates, GDP per capita, and employment statistics in 2023 reflect the real impact of these technological advances.In 2023, China's provincial GDP growth rates exhibited a diverse range of economic performances. The most robust growth was observed in Tibet and Hainan, with growth rates of 9.5% and 9.2% respectively, reflecting significant economic dynamism in these regions. Conversely, Heilongjiang experienced the lowest growth at 2.6%, indicating regional disparities in economic development. Provinces like Guangdong and Jiangsu, despite being economic powerhouses, reported moderate growth rates of around 4.0%, suggesting a stabilisation in their economic expansion. Overall, the varied growth rates across the provinces underscore the multifaceted nature of China's economic landscape, where regional policies and industries play crucial roles in shaping economic outcomes. And In 2023, the economic landscape across China's provinces showcased marked disparities in per capita GDP. The wealthier eastern coastal regions like Beijing, Shanghai, and Jiangsu led with the highest per capita GDP figures, reflecting their advanced economic development and higher living standards. On the other hand, less developed provinces such as Gansu and Heilongjiang recorded the lowest per capita GDP, indicating ongoing challenges in economic development. This distribution underscores the varied economic conditions across China, with coastal areas continuing to outperform due to better industrialization, access to international markets, and higher levels of investment.

The interplay between data infrastructure development and economic performance is a vivid example of two-way empowerment. Enhanced data capabilities enable more precise market analysis and more informed investment decisions, promoting not only immediate economic growth, but also long-term sustainability. As China's data capabilities continue to increase, data-driven decision-making capabilities have significantly improved, and productivity and innovation capabilities in high-tech and manufacturing industries have continued to increase. The growth of data infrastructure promotes economic development and embodies the dynamics of two-way empowerment. Investment and consumption indicators, such as levels of public and private investment and consumer spending, especially in these advanced industries, are both driven and driven by advances in data infrastructure. This synergy promotes broader economic growth and human resource development. In addition, the volatility of employment data reflects economic challenges and recovery dynamics, highlighting the critical role of high-quality data in developing strong economic strategies and sustainable development. This interconnectedness highlights the transformative impact of digital integration on the modern economy, illustrating the cycle of increased data capabilities leading to smarter investment decisions and further technological innovation. In summary, the development of China's digital infrastructure is both a driver and a beneficiary of economic development, illustrating a mutually reinforcing cycle in which advanced data capabilities grow and are enhanced by economic growth. This holistic approach not only addresses current economic needs, but also lays the foundation for sustainable development, making China a case study in the transformative impact of digital integration across the country.

3.2 Data analysis

Using cross-sectional data analysis, this paper examines the impact of economic and social data on the Data Development Index (DDI) for 31 provincial-level administrative regions in China in 2023. In order to achieve this research purpose, before using EViews software for statistical analysis, we first normalise all data and screen missing values and outliers to ensure the accuracy and reliability of data analysis.

This time, through studying the research data of 31 provinces in China, using 31 sample data for analysis, using the found data for descriptive statistics, correlation analysis, multicollinearity test, regression analysis, heteroscedasticity test, residual normal distribution and other tests, descriptive statistics show how the data used in this paper is, and the fluctuation range of the data. The average trend of data, correlation analysis, etc., learns how the preliminary correlation between variables is, that is, the simple quantitative relationship between two variables, and verifies whether there is a high degree of multicollinearity between variables. Then, regression analysis is carried out to show how the relationship between the data in the case of adding multiple variables is more accurate than correlation. Therefore, the significance and influence direction of explanatory variables are measured, and heteroscedasticity test and residual normal distribution are carried out to verify the reliability of regression results.

Establishment of model

To study the impact of UNE (unemployment rate), GDPG (GDP growth rate) and LNPGDP (natural logarithm of GDP per capita) on DDI.

$$DDI_t = \alpha_0 + \alpha_1 UNE_t + \alpha_2 GDPG_t + \alpha_3 LNPGDP_t + \varepsilon_t$$

The above $\alpha0$ is the intercept term, which $\alpha1$ is the influence coefficient. Its value is positive, which means that the increase of explanatory variables will lead to the increase of DDI; its value is negative, which means that the increase of explanatory variables will lead to the decrease of DDI; The remaining variables are similar to inference, and εt is a random error term, which contains the influence of other variables not considered in this paper.

Descriptive statistics

As follows, the variables added to the model in this paper are measured. At the same time, the situation of all variables, the fluctuation range, the degree of fluctuation and the average value are understood, so as to understand whether the data processed in this paper is reasonable:

Tabe 2: Descriptive Statistical Analysis

'ariables	lean	ledian	laximum	linimum	td. Dev.	kewness	urtosis
DDI	.4126	.4300	.5900	.2600	.1064	.4435	.2106
UNE	.8871	.9000	.9000	.4000	.5084	).6043	.8596
GDPG	.5387	.3000	.5000	.6000	.4193	.9497	.5670
LNPGDP	.3564	.2562	0.2549	.8236	.3702	.8608	.0463

Note: The dispersion coefficients mentioned below are standard deviation/mean, the higher the value, the greater the fluctuation.

The number of samples is 31, indicating that there is no missing data, which has been processed in advance. The mean value of DDI is 0.4126, the fluctuation range is 0.2600 and 0.5900, the fluctuation range is not large, and the standard deviation is 0.1064, which is also far less than the mean value, and the dispersion coefficient is low. The fluctuation range of UNE is 2.4000-4.9000, with an average value of 3.8871, which is biassed towards the maximum value; the average value of GDPG is 5.5387, and the minimum value is also greater than 0; the average value of natural logarithm of per capita GDP is 9.3564, which is not a big fluctuation.

Correlation analysis

The measure of correlation analysis can preliminarily determine whether the relationship between variables is significant according to the t test of correlation analysis (whether there is an asterisk automatically output by software), and determine the direction of correlation between variables according to the positive and negative correlation coefficients. If it is positive, it changes in the same direction; otherwise, it changes in the reverse direction; and the higher the absolute value of correlation coefficient, the higher the correlation will be. But correlation is only the relationship between the two and, therefore, serves only as a basis for preliminary judgement.

Table 3: Correlation analysis

	DDI	UNE	GDPG	LNPGDP
DDI	1.0000			
UNE	0.3278*	1.0000		
GDPG	-0.4667***	-0.0090	1.0000	
LNPGDP	0.6798***	0.3475*	-0.2594	1.0000

Note: *, **, *** indicates passing the test at the significance level of 10%, 5%, 1%. The more asterisks, the higher the probability of passing the test.

The correlation coefficient between UNE and DDI is 0.3278, which is significant at the significance level of 10%. The increase of UNE will lead to the increase of DDI, but due to the inaccuracy of correlation analysis, the relationship between variables needs to be more accurate when more factors are controlled. Therefore, it needs to be verified by subsequent regression. Similarly, there is a significant negative correlation between GDPG and DDI, and a significant positive correlation between LNPGDP and DDI. In addition to the first column, the absolute value of the correlation coefficient from the second column to the last column is up to 0.3475, which does not exceed the critical value 0.8. Therefore, the collinearity of the model is not serious, and regression analysis can be carried out without interference.

Regression analysis

Multiple linear regression analysis was used to verify the relationship between the variables.

Table 4 : Model regression result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.0401***	0.3714	-2.8005	0.0093
UNE	0.0280	0.0283	0.9889	0.3315
GDPG	-0.0242**	0.0099	-2.4568	0.0207
LNPGDP	0.1580***	0.0403	3.9196	0.0005
R-squared	0.5682			
Adjusted R-squared	0.5203			
F-statistic	11.8447			
Prob(F-statistic)	0.0000			

Note: *, **, *** indicates passing the test at the significance level of 10%, 5%, 1%. The more asterisks, the higher the probability of passing the test.

The R square of the model is the judgement of goodness of fit, but for different data types, the value is different. This time, cross-section data is used, and the degree of fitting is 56.82%, which is good, while the F-test value is the judgement of the significance of the overall model. If the overall model is not significant, it is unnecessary to conduct further research and analysis. There is a probability of more than 99% that the model with DDI as the explained variable passes the test, UNE's influence on DDI is not significant, GDPG's regression coefficient on DDI is -0.0242, which is significant, there is a probability of more than 95% that the influence of GDPG passes the test, every time GDPG increases by 1 unit, The average decrease of DDI will be 0.0242, while the impact coefficient of LNPGDP is 0.1580, which is significant at the significance level of 1%. The increase of LNPGDP will lead to the increase of DDI, and the average increase of DDI will be 0.001580 for every 1% increase of PGDP.

Heteroscedasticity test

White test is used to verify whether the model has heteroscedasticity, that is, whether the residual passes the test.

Table 5 : White Test

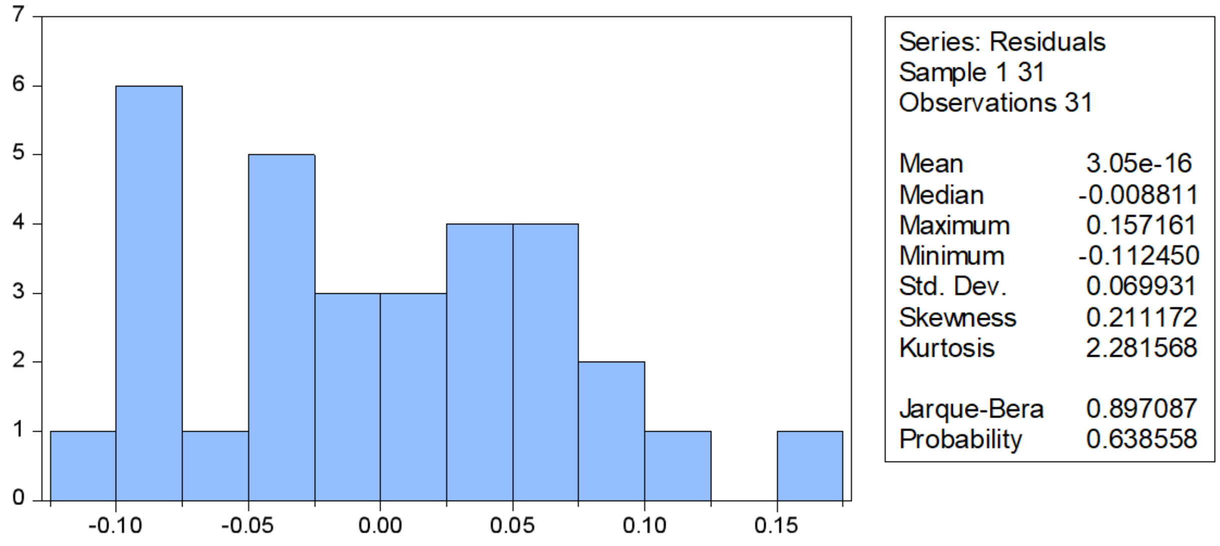
Heteroskedasticity Test: White			
F-statistic	0.6018	Prob. F(9,21)	0.7815
Obs*R-squared	6.3561	Prob. Chi-Square(9)	0.7038
Scaled explained SS	3.0897	Prob. Chi-Square(9)	0.9606

In this case, the chi-square value is 6.3561, and the corresponding P-value is 0.7038, which is greater than 0.05. Therefore, the null hypothesis that the residual is homoscedasticity is accepted, that is, there is no heteroscedasticity in the model.

Normality test

Histograms are used to verify whether the residuals follow normal distribution.

Table 6 : Histogram



At this time, the JB statistic value is 0.8971, and the P-value is 0.6386, which is greater than 0.05. Therefore, the original hypothesis of normal distribution of residual is accepted, that is, the residual is in normal distribution.

3.3 Hypothesis Testing

This study employs a hypothesis testing framework, using EViews software to statistically analyze data from 31 provincial-level administrative regions in China. The objective is to rigorously assess the following hypotheses concerning the impact of data resource development on economic and human resource development:

- **$H0_1$: There is no positive correlation between the level of data development and local economic performance.**
- **$H1_1$: There is a positive correlation between the level of data development and local economic performance.**
- Regression analysis reveals a significant positive correlation between the Data Development Index (DDI) and local economic performance (measured by the natural logarithm of GDP per capita) (β=0.1580,p<0.01\beta = 0.1580, p < 0.01β=0.1580,p<0.01), leading us to reject $H0_1$ and accept $H1_1$.
- **$H0_2$: The enhancement of data resources does not significantly impact economic development.**
- **$H1_2$: The enhancement of data resources significantly impacts economic development.**
- An in-depth analysis of data flow efficiency and the level of data infrastructure construction shows significant relationships with improvements in regional economic indicators, thus supporting $H1_2$ and rejecting $H0_2$.
- **$H0_3$: There is no positive correlation between data flow efficiency and the level of data infrastructure construction.**
- **$H1_3$: There is a positive correlation between data flow efficiency and the level of data infrastructure construction.**
- Results indicate a significant positive correlation between data flow efficiency (measured by metrics such as data centre presence and network coverage) and the level of data infrastructure construction (measured by regional investments in and progress of data infrastructure), confirming the validity of $H1_3$ and leading to the rejection of $H0_3$.

Through the validation of these hypotheses, this research clarifies the crucial role of data resource development and infrastructure construction in driving local economic growth and human resource development. These findings provide a basis for policymakers, emphasising the importance of strategic measures in the management and utilisation of data resources. Future research could further explore the impact of data resources on specific economic sectors or human resource management practices to more comprehensively understand and leverage the potential of data.

4. RESULTS AND DISCUSSION

This study conducted a thorough statistical analysis using EViews software on data from 31 provincial-level administrative regions in China, revealing the complex relationships between data resource development and both local economic and human resource development. The results demonstrate a significant positive correlation between the level of data development and local economic performance, particularly in regions with well-developed data infrastructure.

Data-Driven Economic Development

Regression analysis indicates a significant positive correlation between the Data Development Index (DDI) and the natural logarithm of GDP per capita (LNPGDP) (β=0.1580,p<0.01\beta = 0.1580, p < 0.01β=0.1580,p<0.01), suggesting that the optimization and utilisation of data resources correlate positively with regional economic prosperity. These findings underscore the importance of constructing robust data infrastructure and enhancing the efficiency of data flows, providing policymakers with evidence to advocate for data-driven economic development strategies.

Data Empowerment in Human Resources

Although the impact of the unemployment rate (UNE) on DDI was not statistically significant (β=0.0280,p>0.05\beta = 0.0280, p > 0.05β=0.0280,p>0.05), this outcome suggests that further research is needed into how data resources can enhance job quality and labour market efficiency to promote human resource development. The application of data not only optimises talent management systems but also increases the effectiveness of targeted training and education, thereby enhancing overall workforce productivity.

Policy Recommendations

Given the significant dual empowering effect of data resources on economic and human resource development, policymakers are advised to:

- Strengthen the construction and maintenance of data infrastructure, especially in regions where data infrastructure is relatively underdeveloped.
- Promote open and equitable access to and use of data resources across all industries, particularly for small businesses and startups.
- Support data-driven educational and training programs to enhance workforce skills and adaptability to future market demands.

Directions for Future Research

Future studies should consider expanding to more countries or different types of economies to compare how data resource development and utilisation impact economic and human resource development in various cultural and political contexts. Moreover, a deeper analysis of how data security and privacy protection can facilitate data sharing while safeguarding individual and corporate interests is also a vital direction for future research.

Through the empirical analysis conducted in this study, we have obtained robust evidence of the dual empowerment role of data resources in fostering economic growth and human resource development. These findings are not only of significant theoretical relevance but also provide practical guidance and references for local governments, businesses, and policymakers in formulating relevant strategies and policies.

5. POLICY IMPLICATIONS

The findings of this study have several important implications for policymakers, especially in regions like China where data infrastructure plays a critical role in economic and human resource development:

1. Investment in Data Infrastructure: Given the strong correlation between data development and economic performance, governments should prioritise investments in data infrastructure. This includes not only the physical aspects, such as data centres and network capabilities but also the regulatory frameworks that promote data security, privacy, and ethical use.
2. Data Literacy and Education: To maximise the benefits of data resources, there is a need for substantial investment in data literacy programs across all levels of education. This will ensure a workforce capable of leveraging big data analytics, contributing to both economic growth and innovative human resource practices.
3. Encouraging Data-Driven Innovation: Policymakers should foster an environment that encourages data-driven innovation within businesses and public services. This can be achieved through incentives for businesses to adopt advanced data analytics and by integrating data-driven decision-making processes into public sector projects.
4. Balancing Access and Privacy: While promoting the use of data resources, it is crucial to balance this with robust data protection policies to protect individuals' privacy and build public trust in data systems.
5. Regional Policy Tailoring: The variability in data infrastructure across different regions suggests the need for policies that are tailored to the specific needs and capacities of each region. This approach can help mitigate disparities and promote equitable economic growth.

6. CONCLUSIONS

This study employed data from China to investigate the diverse role of data resources in economic and human resource development, revealing a substantial positive association between data development and economic well-being. The results support the idea that efficient administration and utilization of data resources can accelerate local economic performance, especially in regions with well-established data infrastructure.

Using EViews for econometric analysis, this research has verified that data development not only directly helps to economic growth but also plays a vital role in increasing human resource development by improving employment possibilities and workforce capabilities. These results offer strong empirical evidence to support the promotion of data-driven solutions in economic policy and human resource management.

The report highlights the importance of taking a proactive approach to utilizing the power of data for sustainable development, as data continues to reshape global economies. To fully harness the economic and human development benefits of data resources, governments and businesses should persist in investing in and enhancing data infrastructure and policies.

7. ACKNOWLEDGEMENT

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Appendix :

Table GDP growth rate, per capita GDP, unemployment rate data of 32 provinces or regions in China in 2023 https://docs.google.com/document/d/19LsufEmYBirzbAzfmqbrwOtE5HGAk6vI/edit?usp=drive_link&ouid=116849977163128131351&rtpof=true&sd=true