

PAPER

The Driving Effect of Interactive Mobile Technology on Digital Economy Based on PLS-SEM

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ABSTRACT

This paper studies the driving effect of mobile technologies for human-computer interaction on the digital economy, taking interactive mobile technologies as exogenous variables and the user scale, innovation capability, and industrial development of the digital economy as endogenous variables. Using panel data of interactive mobile technologies and the digital economy from 120 monthly periods in China between 2014 and 2023 as the data source, an empirical analysis is conducted by constructing a partial least squares structural equation modeling (PLS-SEM). The research findings show that interactive mobile technologies have a significant positive impact on the user scale and innovation capability of the digital economy, while interactive mobile technologies have no significant direct driving effect on industrial development, which needs to be indirectly influenced through innovation capability and user scale. Therefore, the research conclusion of this paper holds that to promote the industrial development of the digital economy, it is necessary to expand the user scale through interactive mobile technologies and enhance the innovation capability through patent transformation, scientific and technological investment, etc.

KEYWORDS

interactive mobile technology, digital economy, partial least squares structural equation modeling (PLS-SEM), driving effect

1 INTRODUCTION

At present, the digital economy has become an important component of social and economic development, and countries around the world are striving to develop the digital economy, hoping to adjust and optimize industrial structures through the transformation of digital economic development [1]. According to data released by the China Academy of Information and Communications Technology (CAICT), the total volume of China's digital economy reached 53.9 trillion yuan in 2023, accounting for nearly 40% of GDP [2]. The total development volume of China's digital economy is shown in Figure 1.

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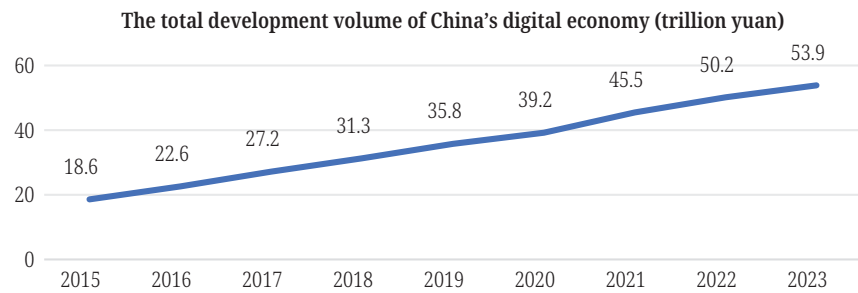


Fig. 1. Total development volume of China's digital economy

With the rapid development of new technologies represented by AI, interactive mobile technologies have also advanced rapidly. These technologies cover multiple fields such as computer science and communication technology. Interactive technologies have evolved from early keyboard input and touch screens to current voice recognition, gesture recognition, VR/AR, etc. These new interactive recognition methods are continuously cultivating people's new operation habits. Meanwhile, this new and efficient interaction mode injects fresh vitality into the development of the digital economy [3].

Although the promoting effect of these new interactive mobile technologies on the digital economy has been widely recognized in academia, there are still gaps in the study of the internal driving mechanisms among interactive mobile technology, digital economy user scale, digital economy innovation capability, and digital economy industrial development [4]. In particular, research on quantitative analysis of multi-factor interactive influences and action paths is insufficient [5]. To address this issue, this paper uses PLS-SEM to study the influence relationships among them, identify core factors and potential mechanisms of their interactions, and provide solid theoretical and practical foundations for the high-quality and sustainable development of the digital economy.

2 LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 Interactive mobile technology and digital economy user scale

Some scholars argue that the popularization of mobile devices and improvements in interactive technologies significantly drive consumer markets [6]. For example, a mobile e-commerce platform app uses extensive interactive technologies to implement VR product displays, attracting large numbers of consumers and merchants to settle in [7]. The use of interactive mobile technologies by e-commerce platforms can also attract numerous users to download the app, increase daily active user counts, generate social fission communication effects, and thus promote the growth of digital economy user scale [8].

Hypothesis H1: Interactive mobile technology has a significant positive impact on the scale of digital economy users.

2.2 Interactive mobile technology and digital economy innovation capability

Innovations in human-computer interaction technologies can promote the development of digital industries and optimize digital economic structures. Enterprises mine market demands and consumer preferences to obtain massive valuable data, which can be used for product and service model training. Meanwhile, the application of these technologies has generated personalized recommendation services such as “thousands

of people, thousands of faces,” effectively enhancing the innovative vitality of the digital economy [9]. Additionally, mobile technology enthusiasts establish mobile application development communities where they share source codes, post development experiences, and jointly promote the innovative development of mobile applications [10]. Enterprises can also collect real-time user feedback through apps to quickly adjust products and services, thereby improving the innovation capability of the digital economy [11].

Hypothesis H2: Interactive mobile technology has a significant positive impact on the innovation capability of the digital economy.

2.3 Interactive mobile technology and digital economy industrial development

Interactive mobile technologies use big data analysis and intelligent algorithms to accurately match supply and demand information, improving resource allocation efficiency. For example, the Didi APP can dispatch the most suitable vehicles based on users’ travel locations, destinations, and real-time vehicle position information, reducing empty driving rates [12]. Furthermore, the widespread popularity of interactive mobile payments allows consumers to complete payments quickly on apps, greatly reducing transaction costs [13].

Hypothesis H3: Interactive mobile technology has a significant positive impact on the industrial development of the digital economy.

2.4 Interactions within the digital economy

A large mobile user base provides rich demands for digital economic development, thus driving the growth of digital industries. Enterprise innovation capabilities also drive companies to develop new products to attract more consumers, expanding the user base and improving corporate profitability. Advances in technology companies further promote digital industrial upgrading, while digital industrial development creates a favorable environment for expanding mobile user scales and enhancing enterprise innovation capabilities [14].

Hypothesis H4: The scale of digital economy users has a significant positive impact on the innovation capability of the digital economy.

Hypothesis H5: The innovation capability of the digital economy has a significant positive impact on the industrial development of the digital economy.

3 RESEARCH METHODS

3.1 Research model

This paper studies the driving effects among interactive mobile technology, digital economy user scale, innovation capability, and industrial development. Since PLS-SEM is suitable for analyzing non-normally distributed variables and focuses more on prediction-oriented analysis, this paper plans to use PLS-SEM for research and analysis.

The measurement model and structural model formulas are:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \zeta \quad (1)$$

Among them, Y represents the endogenous latent variable; X_1, X_2, \dots, X_n are exogenous latent variables; $\beta_1, \beta_2, \dots, \beta_n$ are the corresponding path coefficients of exogenous latent variables on the endogenous latent variable; ζ is the error term, that is, the part of the variation of the endogenous latent variable that cannot be explained by the linear combination of these exogenous latent variables.

The structural path diagram is shown in Figure 2.

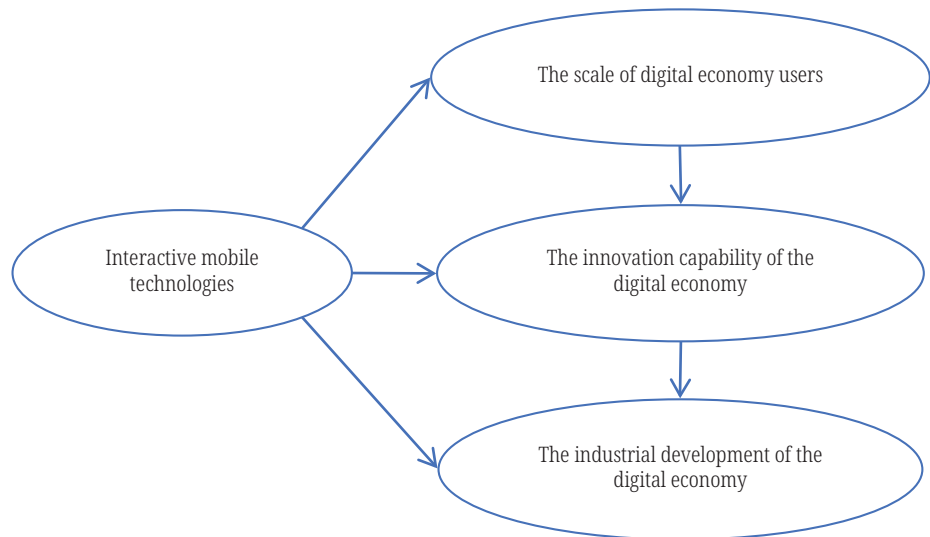


Fig. 2. Structural path diagram

3.2 Variables

Exogenous latent variable: Interactive Mobile Technology. To comprehensively and accurately measure the development level of mobile technology, a multi-dimensional indicator system is planned. Based on data from the China Urban and Rural Construction Statistical Yearbook (CURCSY), CAICT, etc., indicators such as mobile phone penetration rate, daily mobile APP downloads, daily mobile APP usage duration, and daily active users of each mobile APP are collected for 120 monthly periods in China from 2014 to 2023, constructing a quantitative indicator that comprehensively reflects the development status of interactive mobile technology. As shown in Table 1.

Table 1. Evaluation system for exogenous latent variable—Interactive mobile technology

Exogenous Latent Variable	Observed Variable	Unit	Direction
Interactive Mobile Technology (IMT)	Mobile Phone Penetration Rate (MP)	Units/100 People	+
	Daily Mobile APP Downloads (AD)	Hundreds of Millions of Times	+
	Daily Mobile APP Usage Duration (MD)	Hundreds of Millions of Hours	+
	Daily Active Users of Mobile APPs (MU)	Hundreds of Millions of Person-Times	+

Endogenous latent variables: Digital Economy User Scale, Digital Economy Innovation Capability, Digital Economy Industrial Development. The measurement indicators for the digital economy user scale involve collecting variables such as scientific and technological innovation investment, digital inclusive finance, added value of secondary and tertiary industries, and express delivery volume from the

panel data of NBS, Ministry of Industry and Information Technology (MIIT), CAICT, etc. These variables are derived from 120 monthly periods in China between 2014 and 2023 to calculate the overall development of the digital economy, as shown in Table 2.

Table 2. Evaluation system for endogenous latent variables—Digital economy

Endogenous Latent Variable	Observed Variable	Unit	Direction
Digital Economy User Scale (DUS)	Number of Web Pages (WQ)	Hundreds of Millions	+
	Number of Domain Names (DN)	Ten Thousand	+
	Internet Broadband Access Rate (IA)	%	+
	Internet Penetration Rate (IP)	%	+
	Per Capita Telecom Business Volume (PT)	Yuan/Person	+
Digital Economy Innovation Capability (DIC)	Number of Legal Entities in Information Transmission, Software and Information Technology Services (NL)	Ten Thousand	+
	Proportion of Employment in Information Software Industry (PE)	%	+
	Number of Domestic Patent Authorizations (DQ)	Ten Thousand	+
	Number of Domestic Patent Applications Accepted (DA)	Items	+
	Investment in Scientific and Technological Innovation (IS)	Hundreds of Millions of Yuan	+
Digital Economy Industrial Development (DID)	Digital Inclusive Finance (DF)	Hundreds of Millions of Yuan	+
	Proportion of Enterprises with E-commerce Transaction Activities (EC)	%	+
	E-commerce Sales (ES)	Trillions of Yuan	+
	Added Value of Secondary and Tertiary Industries (ST)	Trillions of Yuan	+
	Express Delivery Volume (ED)	Hundreds of Millions of Pieces	+

According to the above evaluation system, the measurement model diagram is drawn as shown in Figure 3.

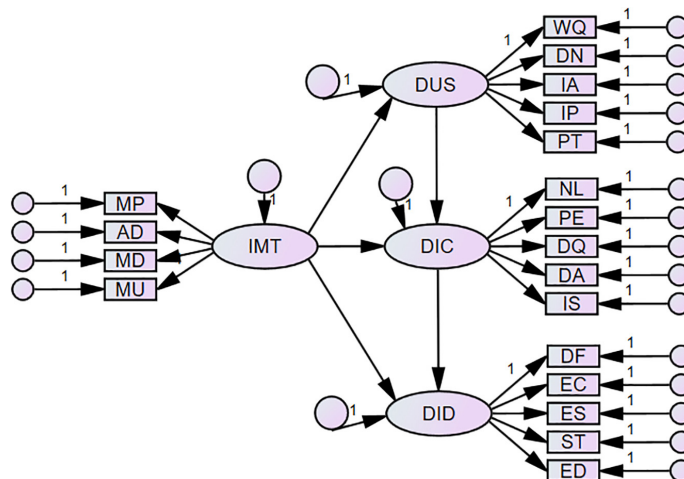


Fig. 3. Measurement model diagram

3.3 Data collection

The quantitative indicators of the development status of mobile technology, based on data from the CURCSY, CAICT, and other sources, are shown in Table 3 through the aggregated data of 120 monthly periods in China from 2014 to 2023.

Table 3. Development status of mobile technology

Observed Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
MP	92	94	97	104	113	115	115	118	121	126
AD	256	277	302	337	400	412	416	516	563	615
MD	7012	8947	11392	13500	16925	18748	22121	24363	25834	26918
MU	3.7	4.6	5.6	6.3	7.7	8.8	9.6	10.5	11.1	11.9

The quantitative indicators of the digital economy user scale, based on digital economy panel data from NBS, MIIT, CACIT, and other sources, are shown in Table 4 through the aggregated data of 120 monthly periods in China from 2014 to 2023.

Table 4. Development status of digital economy user scale

Observed Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
WQ	1899	2122	2360	2604	2816	2978	3155	3350	3588	3820
DN	1894	2862	3114	3387	3526	3553	3689	3757	4106	5008
IA	29.4	40.9	51.1	56	62.4	66.2	69	74.9	78.9	83.7
IP	14.1	17.7	20.1	23.9	28.4	31.7	34	38	42	45.7
PT	1166	1272	1292	1356	1360	1737	2045	4839	7974	10226

The quantitative indicators of the digital economy innovation capability, based on digital economy panel data, are shown in Table 5 through the aggregated data of 120 monthly periods in China from 2014 to 2023.

Table 5. Development status of digital economy innovation capability

Observed Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
NL	28.9	38.8	50.8	71.9	92	104.7	128.6	148.8	174.7	203.2
PE	1.7	1.8	1.8	2	2.1	2.3	2.5	2.6	2.7	2.7
DQ	119	158	161	171	232	246	350	352	418	445
DA	218	262	328	351	412	417	499	504	516	536
IS	9254	10013	10944	12012	12954	13971	15271	17514	19361	20969

The quantitative indicators of the digital economy's industrial development, based on digital economy panel data, are shown in Table 6 through the aggregated data of 120 monthly periods in China from 2014 to 2023.

Table 6. Development status of digital economy industrial development

Observed Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
DF	5572	6820	7142	8431	9306	10035	10577	11134	11705	12292
EC	6.3	9.1	9.2	9.4	9.6	9.7	10.3	10.5	10.8	12.9
ES	8	9.2	10.7	13	15.2	16.9	18.9	22.8	30.2	36.4
ST	59	63	69	77	85	91	93	106	111	116
ED	139	206	312	400	507	635	833	1082	1105	1320

4 RESEARCH RESULTS

Partial least squares structural equation modeling mainly focuses on predictive ability. This paper uses data analysis software for analysis, and the model fitting effect table, standardized regression weight table of exogenous latent variables (measurement model), standardized regression weight table of endogenous latent variables (measurement model), effect decomposition table, and path coefficient table between latent variables are obtained, as shown in Tables 7–11.

Table 7. Model fitting effect table

Indicator	Judgment Standard	Calculation Result	Evaluation
SRMR	< 0.08	0.062	Good
NFI	> 0.9	0.91	Good
R ² (DUS)	–	0.79	Excellent
R ² (DIC)	–	0.85	Excellent
R ² (DID)	–	0.76	Good
Model predictive validity			The model has good predictive effectiveness

Note: The R² of DID is 0.76, indicating that 76% of the variance is explained.

Table 8. Standardized regression weights table of exogenous latent variables (Measurement model)

Latent Variable	Observed Variable	Factor Loading	T-Value	Significance
IMT	MP	0.82	15.21	Established
	AD	0.93	32.17	Established
	MD	0.88	20.45	Established
	MU	0.86	18.93	Established

Table 9. Standardized regression weights table of endogenous latent variables (Measurement model)

Latent Variable	Observed Variable	Factor Loading	T-Value	Significance
DUS	WQ	0.81	12.35	Established
	DN	0.78	10.21	Established
	IA	0.92	25.67	Established
	IP	0.89	19.82	Established
	PT	0.71	8.94	Established

(Continued)

Table 9. Standardized regression weights table of endogenous latent variables (Measurement model) (Continued)

Latent Variable	Observed Variable	Factor Loading	T-Value	Significance
DIC	NL	0.94	35.12	Established
	PE	0.83	14.56	Established
	DQ	0.76	11.23	Established
	DA	0.72	9.87	Established
	IS	0.85	16.78	Established
DID	DF	0.79	13.45	Established
	EC	0.82	15.67	Established
	ES	0.91	28.91	Established
	ST	0.74	10.32	Established
	ED	0.87	21.04	Established

Note: The factor loading of all indicators is > 0.7, indicating that the measurement model has excellent quality.

Table 10. Effect decomposition table

Path	Direct Effect	Indirect Effect	Total Effect
IMT → DUS	0.84	–	0.84
IMT → DIC	0.47	$0.84 \times 0.39 = 0.33$	0.80
IMT → DID	0.09	$0.47 \times 0.73 + 0.33 \times 0.73 = 0.58$	0.67
DUS → DIC	0.39	–	0.39
DUS → DID	–	$0.39 \times 0.73 = 0.28$	0.28
DIC → DID	0.73	–	0.73

Among them:

The indirect effect of IMT on DID (0.58) >> direct effect (0.09)

Core mediating paths:

IMT → DIC → DID (effect = $0.47 \times 0.73 = 0.34$)

IMT → DUS → DIC → DID (effect = $0.84 \times 0.39 \times 0.73 = 0.24$)

Table 11. Path coefficient table between latent variables

Path	Standardized Coefficient	S.E.	C.R.	P
IMT → DUS (H1)	0.84	0.04	21.00	***
IMT → DIC (H2)	0.47	0.11	4.27	***
IMT → DID (H3)	0.09	0.13	0.69	0.490
DUS → DIC (H4)	0.39	0.09	4.33	***
DIC → DID (H5)	0.73	0.07	10.43	***

Notes: C.R. > 1.96 indicates P < 0.05 significance.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study empirically analyzes the driving effect of interactive mobile technology on the digital economy by constructing PLS-SEM. The research shows that interactive mobile technologies have a significant positive impact on the user scale and innovation capability of the digital economy, while interactive mobile technologies have no significant direct driving effect on industrial development, which needs to be indirectly influenced through innovation capability and user scale. As shown in Table 12.

Table 12. Hypothesis verification results

Hypothesis	Path	Result
H1	Interactive Mobile Technology → Digital Economy User Scale	Accepted
H2	Interactive Mobile Technology → Digital Economy Innovation Capability	Accepted
H3	Interactive Mobile Technology → Digital Economy Industrial Development	Rejected
H4	Digital Economy User Scale → Digital Economy Innovation Capability	Accepted
H5	Digital Economy Innovation Capability → Digital Economy Industrial Development	Accepted

Core driving chain:

Interactive mobile technology → digital economy innovation capability → digital economy industrial development (total effect = 0.34)

Interactive mobile technology → digital economy user scale → digital economy innovation capability → digital economy industrial development (total effect = 0.24)

Table 11 shows that the direct effect of H3 “IMT → DID” is not significant, but the indirect effect (0.58) is significant. “Interactive mobile technology needs to indirectly promote industrial development (total effect 0.67) by improving user scale (0.84) and innovation capability (0.47),” which confirms the transmission chain of “technology – user – innovation – industry” in the digital economy.

5.2 Recommendations

Expand the digital economy user scale by enhancing interactive mobile technology. First, increase capital investment in technological innovation. Governments and enterprises should join hands to invest more resources in R&D and give key support to cutting-edge technology companies in 5G networks, AI algorithms, big data processing, and other fields. For example, providing tax incentives such as a 150% additional deduction of R&D expenses for enterprises in the 5G and AI fields, referring to the model of the “Digital Economy Special Fund” in the Shenzhen Qianhai Free Trade Zone. Meanwhile, special scientific research funds should be set up to fully promote close industry-university-research cooperation between universities, research institutions and enterprises so as to accelerate the transformation of technological innovation achievements from laboratories to practical applications.

Second, make great efforts to advance infrastructure construction. Further strengthen the construction of mobile network infrastructure, especially in remote

and rural areas, to expand network coverage and improve signal stability in these regions.

Third, optimize the user experience. Deeply explore users' real needs and tailor personalized and exclusive products and services for them. Use AI algorithms to conduct in-depth analysis of user behavior data, accurately push content of interest to users, and improve user satisfaction with products.

Strengthen the construction of digital innovation capability. First, incentivize patent transformation. Establish and improve the patent transformation mechanism to encourage enterprises to apply patent technologies to actual production. Governments can reduce the cost of patent transformation and enhance enterprises' enthusiasm through policy tools such as tax incentives and financial subsidies.

Second, guide investment in science and technology. Increase investment in science and technology in the field of digital innovation, and guide social capital to flow into digital economy innovation projects.

Third, cultivate innovative talents. Strengthen the cultivation of digital innovation talents to provide solid talent support for the development of the digital economy. Encourage universities and vocational colleges to strengthen cooperation with banks and enterprises and provide customized talent training services for enterprises. For example, learn from the "Huawei – University Intelligent Base Program" to promote the embedding of interactive technology courses in university training programs.

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