Volume 2, Issue 3, 2025

Print ISSN: 3007-6854
Online ISSN: 3007-6862

Social Science and Management

Social Science and Management

Volume 2, Issue 3, 2025

Published by Upubscience Publisher

Social Science and Management
Print ISSN: 3007-6854 Online ISSN: 3007-6862
Email: info@upubscience.com
Website: http://www.upubscience.com/

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3054

HEALTHY 'FOOD' IN GOOD, FAT REDUCTION NEW TREND-'HEALTHY LOW-CALORIE DIET' UNDER THE BACKGROUND OF GUANGXI BASED ON THE YOUNG GROUP OF LOW-FAT SNACKS CONSUMPTION INTENTION INVESTIGATION AND INNOVATION STRATEGY ANALYSIS

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Abstract: This paper focuses on the trend of 'low-fat low-calorie healthy diet', aiming at the young group of 14-30 years old in Guangxi, and deeply studies the contradiction between high purchase intention and low purchase rate in the low-fat snack market. On the one hand, we hope to fill the current research gap on low-fat snacks, on the other hand, we hope to bring practical promotion to low-fat snacks. Through questionnaires and network data, this paper analyzes consumer value judgments and reveals the market potential and reform needs of low-fat snacks. Five innovative strategies are summarized: product diversification, customized promotion, multi-channel sales, healthy raw material use and brand vision improvement. Logical model and K-means clustering analysis are used to analyze the influence of consumer characteristics on purchase intention, and the target market is subdivided. A neural network model was established, and 18 specific strategies were proposed, covering product taste, health, channel, marketing and packaging innovation, and quantifying their impact on purchase intention. Finally, it puts forward some suggestions for the development of low-fat snack enterprises with high-quality products and honest marketing as the core, and puts forward some suggestions to the government, hoping to contribute to the healthy development of low-fat snack industry.
Keywords: Low fat low card; Guangxi young consumer groups; Logistic model; K-means clustering analysis; Neural network

1 INTRODUCTION

In today 's society, with the awakening of health awareness and the improvement of living standards, healthy low-calorie diet has become a popular lifestyle, especially among young consumer groups. The young generation not only pursues the taste and nutritional value of food, but also pays more attention to the calories and fat content of food[1]. Therefore, the low-fat and healthy characteristics of low-fat snacks make them an ideal choice to meet the health and delicious needs of young consumers, and low-fat snacks are booming[2].
However, the development of the low-fat snack market is not smooth: the quality and variety of low-fat snacks on the market are uneven. Although some products claim to be low-fat, they may contain other ingredients that are not conducive to health, or are difficult to attract consumers due to poor taste and low nutritional value[3]. This poses a new challenge to low-fat snack companies, that is, how to provide high-quality, good-tasting products while meeting health needs.
In terms of theoretical research, the existing literature has confirmed that the popularity of the concept of healthy low-calorie diet has profoundly affected consumers ' purchase behavior[4], prompting consumers to tend to choose low-calorie, low-fat foods. However, consumers ' diverse needs for food taste, quality and price require companies to consider product innovation and market strategies to adapt to market trends and changes in consumer behavior.
From the perspective of consumer behavior, this study will use the innovative neural network analysis method to focus on the young consumer groups in Guangxi, and deeply explore the consumption willingness of low-fat snacks and its influencing factors under the background of healthy low-calorie diet. The research will not only enrich the theoretical system of healthy diet and provide theoretical support for the development of low-fat snack market, but also provide targeted marketing strategies and product innovation suggestions for low-fat snack enterprises, help enterprises to enhance market competitiveness, and provide reference for the government and relevant departments to formulate healthy diet policies.
In the analysis of market status and network public opinion, the low-fat snack market has great potential, and young consumers have become the main driving force of the market. However, online public opinion has a significant impact on consumers ' shopping decisions, and companies need to pay more attention to the authenticity and transparency of product promotion. In the future, with the improvement of global awareness of healthy eating, the low-fat snack market will usher in a broader development prospect, and enterprises will face challenges and opportunities in product innovation, food safety and sustainable development.
In summary, the purpose of this study is to explore the current situation, challenges and opportunities of the low-fat snack market through an in-depth analysis of the willingness of Guangxi adolescents to consume low-fat snacks, and to

provide theoretical basis and practical guidance for promoting the healthy development of the healthy food industry. In order to achieve a win-win situation for enterprises, consumers and the whole society in the new era of healthy eating.

2 RESEARCH DESIGN

2.1 Research Method Description

(1) Descriptive statistic
Through frequency calculation and graphic drawing, this paper understands and analyzes the distribution of respondents' basic characteristics, their willingness to buy low-fat snacks and their tendency to choose innovative strategies.
(2) K-means clustering analysis
Based on the two dimensions of respondents ' preference for low-fat snacks and purchase frequency, this paper clusters respondents to segment the target population of the market and provide data basis for subsequent in-depth analysis.
(3) Logistic regression
This paper uses Logistic regression model to analyze the influence of basic information of young people in Guangxi on the purchase intention of low-fat snacks, and provides suggestions for low-fat snack merchants and producers.
(4) Neural network
This paper uses neural network model to analyze the impact of different innovation strategies on customer purchase intention, and provides reference for enterprises to predict customer behavior.

2.2 Data Sources and Preprocessing

2.2.1 Data sources

In this paper, a survey was conducted on young consumer groups aged 14-30 in Guangxi. A total of 505 questionnaires were collected, of which 468 were valid, and the effective rate of the questionnaire was about 92.67 %. Through online and offline random sampling of seeds and peer-driven sampling to collect questionnaire data. The specific sampling frame is as follows (Table 1):

Table 1 Sample Boxes Specifically Prepared

Overall stratification	First-level unit sampling frame	Sample city	Secondary unit sampling frame	Sampling urban area	Three-level unit sampling frame
East Guangxi	All cities in eastern Guangxi	Wuzhou city	Wuzhou City (District) Center and Town Street Center	Changzhou region	Some young consumer groups in Changzhou District
		Yulin city	Yulin City (District) Center and Town Street Center	Yuzhou district	Some young consumer groups in Yulin Prefecture
		Hezhou city	Hezhou City (District) Center and Town Street Center	Eight-Step district	Some young consumer groups in the eight-step area
Southern Guangxi	All Cities in Southern Guangxi	Qinzhou city	Qinzhou City (District) Center and Town Street Center	Qinnan district	Some young consumer groups in Qinnan District
		Chongzuo city	Chongzuo City (District) Center and Town Street Center	Jiangzhou district	Some young consumer groups in Jiangzhou District
		Fangchenggang city	Fangchenggang City (District) Center and Town Street Center	Fangchenggang district	Some young consumer groups in Fangcheng District
		Beihai city	Beihai City (District) Center and Town Street Center	Haicheng district	Some young consumer groups in Haicheng District
West Guangxi	All cities in western Guangxi	Hechi city	Hechi City (District) Center and Town Street Center	Jinjiang City district	Some young consumer groups in Jinjiang City District
		Baise city	Baise City (District) Center and Town Street Center	Youjiang district	Some young consumer groups in Youjiang District
Northern Guangxi	All cities in northern Guangxi	Guilin city	Guilin City (District) Center and Town Street Center	Lingui district, Xiufeng district	Some young consumer groups in Lingui District and Xiufeng District
		Laibin city	Laibin City (District)	Xingbin district	Some young consumer

			Center and Town Street Center		groups in Xingbin District
		Liuzhou city	Liuzhou City (District) Center and Town Street Center	Liubei district, Chengzhong district	Some young consumer groups in Liubei District and Chengzhong District
Central region of Guangxi	All Cities in Central Guangxi	Nanning city	Nanning City (District) Center and Town Street Center	Xingning district, Qingxiu district	Some young consumer groups in Xingning District and Qingxiu District
		Guigang city	Guigang City (District) Center and Town Street Center	Guigang North district	Some young consumer groups in northern Guangxi

2.2.2 Pre-survey and reliability and validity test

In this pre-survey, 110 questionnaires were randomly distributed to young consumers in 8 cities in the sampling frame. Finally, 96 valid questionnaires were collected, and then the reliability and validity of the questionnaire data were tested to find out the problems.

(1) Reliability test

The reliability test was performed by SPSS software. The results are as follows (Table 2):

Table 2 Reliability Statistics

Cronbach's Alpha	Number of items
0.841	37

The data results show that the overall reliability of the questionnaire is 0.859 greater than 0.80, indicating that the answer to the questionnaire is more reliable.

(2) Validity test

In this paper, KMO and Bartlett spherical test are used to test the structural validity of the questionnaire data through SPSS software. The correlation coefficient of all variables is close to 1, and the correlation between variables is strong. The larger the test value of Bartlett spherical test, the higher the independence between variables, and the more suitable for factor analysis. Before conducting factor analysis, this paper first conducts a sampling adequacy test (Kaiser-Meyer-Olkin, KMO) and Bartlett spherical test to determine the feasibility and rationality of the implementation of factor analysis[5]. Using SPSS software to test the validity, the results are as follows:

Table 3 KMO and Bartlett Spherical Test

KMO and Bartlett tests		
KMO sampling suitability quantity		0.704
Bartlett sphericity test	Approximate chi-square	1653.652
	Degree of freedom	595
	Significance	0.000

Like Table 3, the KMO coefficient is 0.704, and the P-value is approximately 0.000, indicating that it is suitable for factor analysis.

(3) factor analysis

In order to facilitate the subsequent factor analysis, this paper summarizes the following 12 questions in the second part of the questionnaire into three dimensions, which are named as favorability (a1-a2), purchase intention (b3-b7) and strategic preference (c8-c12), like Table 4.

Table 4 Correspondence Table of Variables

Variable name	Corresponding to the questionnaire questions
Favorability a1	8.What is your preference for low-fat snacks?
Favorability a2	14.When low-fat snacks are innovated in all aspects, will you choose to buy?
Purchase intention b3	18. Will you buy low-fat snacks after product innovation?
Purchase intention b4	20. Will you buy low-fat snacks with innovative sales channels?
Purchase intention b5	22.Will you buy low-fat snacks after marketing innovation?
Purchase intention b6	24. Will you buy low-fat snacks with innovative packaging and logo?
Purchase intention b7	26. Will you buy low-fat snacks that are innovative in terms of health?

Strategy preference c8	17.What do you like about product innovation of low-fat snacks?
Strategy preference c9	19.What do you like about the innovation of sales channels for low-fat snacks?
Strategy preference c10	21.What do you like about innovative marketing ideas for low-fat snacks?
Strategy preference c11	23.What do you like about the innovation of packaging and logo of low-fat snacks?
Strategy preference c12	25. What are your favorite health innovations for low-fat snacks?

Factor analysis was performed on the second part of the questionnaire. The questionnaire with structural validity should meet the following two conditions:
1) The common factor should be consistent with the composition of the structural hypothesis in the questionnaire design, and the cumulative variance contribution rate of the common factor should be at least 40 %.
2) Each problem has a higher load value (greater than 0.4) on one of the common factors, and a lower load value on the other common factors. If a problem has a low load value on all factors, it indicates that the meaning it reflects is not clear and should be changed or deleted.

Table 5 Variance Interpretation Table

Total variance explanation						
	Initial eigenvalue			Extract the load sum of squares		
Component	Grand total	Variance proportion	Cumulative %	Grand total	Variance proportion	Cumulative %
1	6.541	18.689	18.689	6.541	18.689	18.689
2	3.495	9.985	28.674	3.495	9.985	28.674
3	2.596	7.418	36.092	2.596	7.418	36.092
4	2.302	6.578	42.670	2.302	6.578	42.670
5	1.997	5.707	48.377			
6	1.664	4.755	53.132			
7	1.453	4.150	57.282			
8	1.278	3.650	60.932			
9	1.121	3.202	64.134			
10	1.085	3.099	67.234			
11	0.976	2.789	70.022			
12	0.935	2.672	72.694			
13	0.881	2.516	75.210			
14	0.856	2.446	77.656			
15	0.713	2.036	79.692			
16	0.680	1.943	81.635			
17	0.653	1.865	83.501			
18	0.594	1.698	85.199			
19	0.566	1.618	86.817			
20	0.527	1.506	88.323			
21	0.458	1.309	89.632			
22	0.443	1.266	90.898			
23	0.394	1.125	92.023			
24	0.359	1.027	93.050			
25	0.335	0.956	94.006			
26	0.326	0.931	94.937			
27	0.318	0.910	95.846			
28	0.261	0.747	96.593			
29	0.222	0.634	97.227			
30	0.220	0.629	97.856			
31	0.184	0.525	98.380			
32	0.166	0.475	98.856			
33	0.150	0.429	99.285			
34	0.131	0.375	99.659			
35	0.119	0.341	100.000			
Extraction method: principal component analysis						

Like Table 5, a total of 4 common factors were extracted. The explained variance of the first 5 common factors was 42.670 %, which met the requirement that the variance contribution rate should be higher than 40 %. After factor rotation, the variance contribution rate of each new common factor changed, but the final cumulative variance contribution rate remained unchanged.

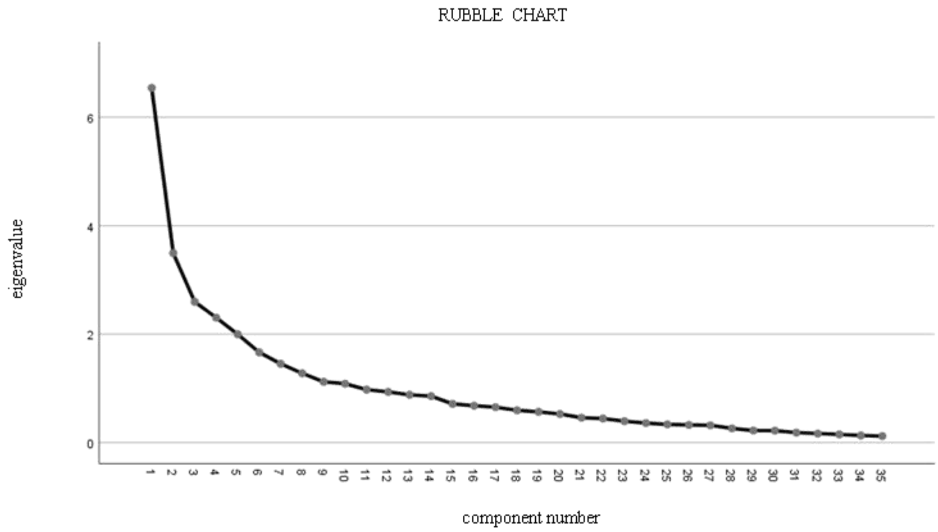

Figure 1 Initial Eigenvalue Gravel Diagram

Like Figure 1, the eigenvalues are arranged in descending order, and the slope between the number of factors 4 and the number of factors 5 becomes slower. The first four factors can already cover most of the information, so the number of factors can be selected as 4, that is, the 12 problems are classified into 4 categories.

Table 6 Rotated Component Matrix

Component matrix a				
	Component			
	1	2	3	4
Favorability a1	-0.157	0.175	0.355	0.431
favorability a2	-0.430	0.029	0.036	0.243
Strategy preference c8	0.107	0.286	-0.367	-0.257
Strategy preference c8	0.142	0.463	0.212	0.183
Strategy preference c8	0.399	0.203	-0.211	0.112
Strategy preference c8	-0.263	0.207	0.659	-0.310
Purchase intention b3	-0.608	-0.101	-0.145	-0.025
Strategy preference c9	0.259	0.602	-0.034	-0.062
Strategy preference c9	0.360	0.407	-0.022	0.058
Strategy preference c9	0.104	0.420	0.024	0.286
Strategy preference c9	0.322	0.450	0.118	0.047
Strategy preference c9	0.229	0.251	0.375	-0.320
Strategy preference c9	-0.572	0.075	0.521	-0.322
Purchase intention b4	-0.634	-0.194	-0.163	-0.101
Strategy preference c10	0.230	0.395	-0.112	-0.389
Strategy preference c10	0.393	0.385	-0.181	0.178
Strategy preference c10	0.370	0.338	0.051	0.005
Strategy preference c10	0.232	0.422	0.182	0.028
Strategy preference c10	-0.491	0.038	0.603	-0.215
Purchase intention b5	-0.558	-0.107	0.046	0.328
Strategy preference c11	0.322	0.387	-0.170	0.026
Strategy preference c11	0.318	0.394	0.036	0.032
Strategy preference c11	0.413	0.358	0.026	-0.111
Strategy preference c11	-0.417	0.296	0.574	-0.091
Purchase intention b6	-0.489	-0.087	0.016	0.358
Strategy preference c12	0.609	-0.315	0.279	0.361
Strategy preference c12	0.511	-0.281	0.337	0.414
Strategy preference c12	0.437	-0.320	0.073	-0.440
Strategy preference c12	0.625	-0.360	0.034	-0.002
Strategy preference c12	0.493	-0.387	-0.062	-0.223
Purchase intention b7	0.595	-0.246	0.295	0.332
Purchase intention b7	0.495	-0.214	0.392	0.339
Purchase intention b7	0.417	-0.279	0.161	-0.365
Purchase intention b7	0.530	-0.290	0.231	-0.116
Purchase intention b7	0.598	-0.306	0.080	-0.369

extraction method: principal component analysis.
a. four components were extracted.

Like Table 6, b7 and c12 variables in factor 1 are relatively large, the load values of c9 ~ c11 variables in factor 2 are relatively large, the load values of b8 variables in factor 3 are relatively large, and the load values of the first six variables in factor 4 are relatively large, indicating that the correlation between variables and their corresponding factors is high. It can be seen that the definition of the factor is clear, which can better represent the meaning of the variable it contains.

3 DESCRIPTIVE ANALYSIS OF THE CURRENT SITUATION OF LOW-FAT SNACKS MARKET

3.1 Analysis of Interviewee Characteristics and Purchase Behavior

After descriptive statistical analysis of the data, it was found that the age of the respondents was mainly between 19 and 23 years old, accounting for more than 50 %, indicating that the young group paid more attention to low-fat snacks. The high proportion of female respondents, nearly two-thirds of the total sample, may be related to the fact that women are more concerned about health and weight management[6]. In terms of education distribution, the proportion of respondents with bachelor 's degree or below (excluding bachelor 's degree) is less than 45 %, which indicates that young consumers with higher education have more understanding and demand for low-fat snacks. In terms of employment, most of the respondents are students, which is consistent with the characteristics of age distribution. The monthly consumption level is mainly concentrated in the range of 1000-2000 yuan, reflecting the economic strength and consumption ability of young consumer groups[7]. The following table shows (Table 7):

Table 7 Respondent Basic Information and Its Proportion

essential information	age	sexuality	employment status	record of formal schooling	monthly consumption level
specific information	19-23 years	female	students in reading	regular college course	1000-2000 yuan
proportion	50.30%	62.77%	64.36%	55.45%	48.51%

In terms of purchase behavior, respondents generally have a high preference for low-fat snacks, but the actual purchase frequency is relatively low, as shown in Figure 2 and Figure 3. This shows that although low-fat snacks have a certain market recognition in the young group, there are still some obstacles to translate into actual purchase behavior. Further analysis found that price, taste and health are the main factors affecting purchase behavior. Most respondents said that if low-fat snacks can provide better taste and reasonable prices while maintaining health, they will be more willing to buy.

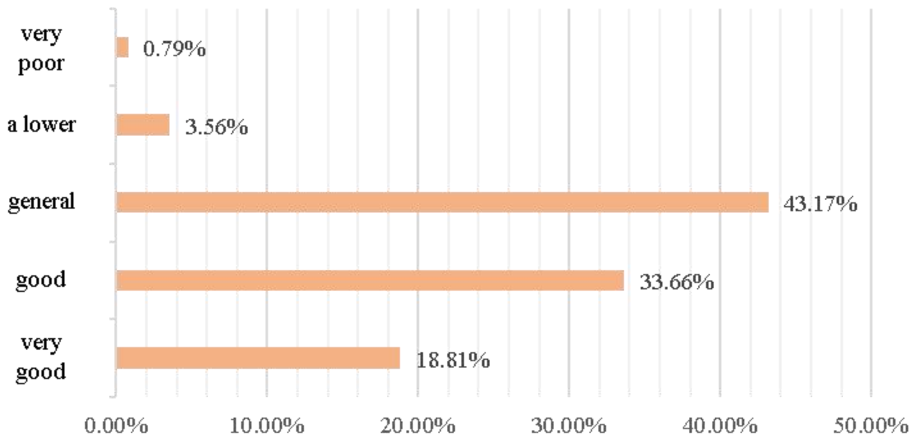

Figure 2 Low-Calorie Snacks Favorability Distribution Map

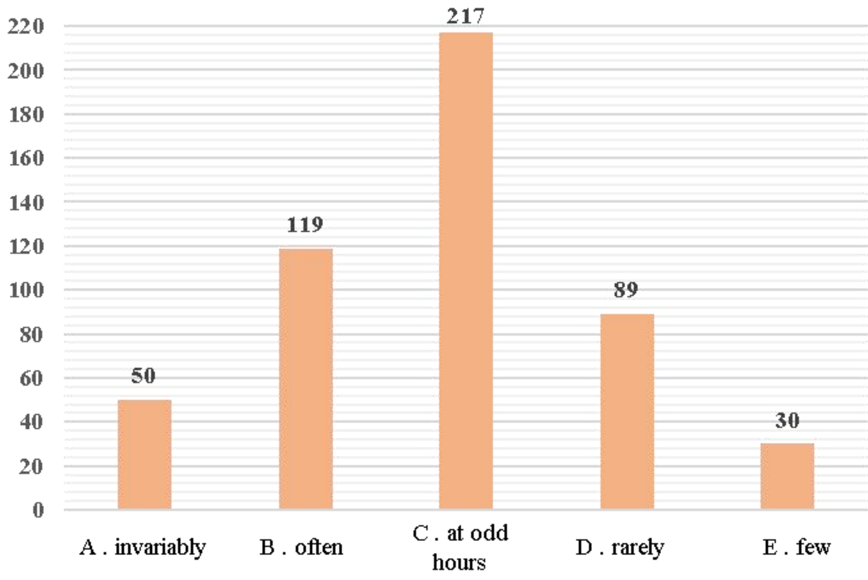

Figure 3 Interviewee Purchase Frequency Chart

3.2 Correlation Analysis between Respondents and Purchase Rate

Original hypothesis H_0: the impact of respondents' basic information on whether to buy low-fat snacks is not significant.
In order to verify this hypothesis, this paper tests the correlation between the basic information of the respondents (such as age, gender, education, etc.) and the purchase rate. Through chi-square test, t test and other statistical methods, it is found that there is a certain correlation between age and gender and purchase rate. As Table 8 shows, young women aged 19-23 are more likely to buy low-fat snacks. The level of education also showed a positive correlation with the purchase rate, and respondents with bachelor's degree were more likely to buy low-fat snacks.

Table 8 Chi-square Test Results

essential information	chi-square value	P	significance
sexuality	-0.072	***	significant
age	2.777	***	significant
record of formal schooling	1.265	***	significant
employment status	2.6	***	significant
monthly consumption level	1.304	0.171	non-significant
city of residence	5.320	0.102	non-significant
BIM	3.135	0.057	non-significant
*p<0.05 **p<0.01 ***p<0.001			

In summary, gender, age, education, employment situation passed the test at a significant level of 5 %, and the basic information of respondents had a certain significant impact on the purchase of low-fat snacks.

4 ANALYSIS OF PURCHASE INTENTION

4.1 Analysis of the influence of customer characteristics on purchase intention based on Logistic regression

This paper uses Logistic model to quantitatively analyze the influence of seven basic information characteristics of young consumers, such as age, gender and education background, on the purchase intention of low-fat snacks after innovation, and puts forward suggestions on product positioning and target market feature selection.
4.1.1 Modeling
In this study, Logistics regression model was used to analyze the influencing factors of young people 's willingness to purchase low-fat snacks after innovation. Age, education and other types of variables using dummy variable processing method[8-9]. 1 means to choose an option, 0 means no choice, and it is included in the model for Logistic regression. The results are shown in Table 9.

Table 9 The Letters of Each Variable Represent the Result

Independent variable letter representation	Chinese meaning of independent variable
Age1	14-18 years old
Age2	19-23 years old

Age3	24-28 years old
Age4	Age: 28 +
Sex1	male
Sex2	female
Edu1	primary school and below
Edu2	junior high
Edu3	high School (including Secondary)
Edu4	college for professional training
Edu5	regular college course
Edu6	postgraduate and above
Job1	Employment situation: students in school
Job2	Employment situation: employed
Job3	Employment situation: other
Con1	Monthly consumption level: 0-1000 yuan
Con2	Monthly consumption level: 1000-2000 yuan
Con3	Monthly consumption level: 2000-4000 yuan
Con4	Monthly consumption level: 4000-6000 yuan
Con5	Monthly consumption level: 6000 yuan or more
City1	Inhabited city: Eastern Guangxi
City2	Inhabited city: Southern Guangxi
City3	Inhabited city: Western Guangxi
City4	Inhabited city: Northern Guangxi
City5	Inhabited city: Central Guangxi
BMI1	BMI ≤ 18.5 (light weight)
BMI2	18.5 ≤ BMI < 24 (healthy weight)
BMI3	24 ≤ BMI < 28 (overweight)
BMI4	BMI ≥ 28 (obesity)

4.1.2 Model application

Table 10 Logistic Regression Model Results

variable	B (standardized coefficient)	standard error	significance	VIF
Age1	0.031	0.037	0.048	2.089
Edu5	0.182	0.113	0.006	0.339
Job1	0.071	0.061	0.030	1.015
Con2	-0.168	0.122	0.041	0.497
City4	-0.003	0.121	0.002	1.001
City5	-0.005	0.286	0.002	0.000
BMI2	0.856	0.844	0.031	1.029

In this study, Age2, Edu5, Job1, Con2, City4, City5 and BMI2 were selected as the benchmark categories, that is, 19-23 years old, undergraduate education, school students, monthly consumption level of 1000-2000 yuan, living in cities in northern and central Guangxi, BIM value 18.5 ≤ BIM < 24. Six variables of age, education level, employment situation, monthly consumption level, living city and BIM value are selected into the model. After Logistic regression, the significance level values of 6 variables such as age and education level were less than 0.05, indicating that the coefficient was statistically significant and statistically significant. The regression results are shown in Table 10.

According to the results in the table, the Logistic regression model is as follows:

$$\mathrm{p}(y) = \frac{1}{1+e^{-x}} \tag{1}$$

$$\mathrm{x} = 0.031\mathrm{Age1} + 0.182\mathrm{Edu5} + 0.071\mathrm{Job1} - 0.168\mathrm{Con2} - 0.003\mathrm{City4} - 0.005\mathrm{City5} + 0.856\mathrm{BMI2} \tag{2}$$

Among them, y represents the willingness to buy, y = 1 represents the willingness to buy low-fat snacks after marketing strategy innovation, and y = 0 represents the unwillingness to buy low-fat snacks after innovation.

The predictive ability of the scoring tool was tested by the area under the receiver operating characteristic (ROC) curve[10]. If the area under the curve is greater than 0.7, the discrimination of the scoring tool is greater (Table 11).

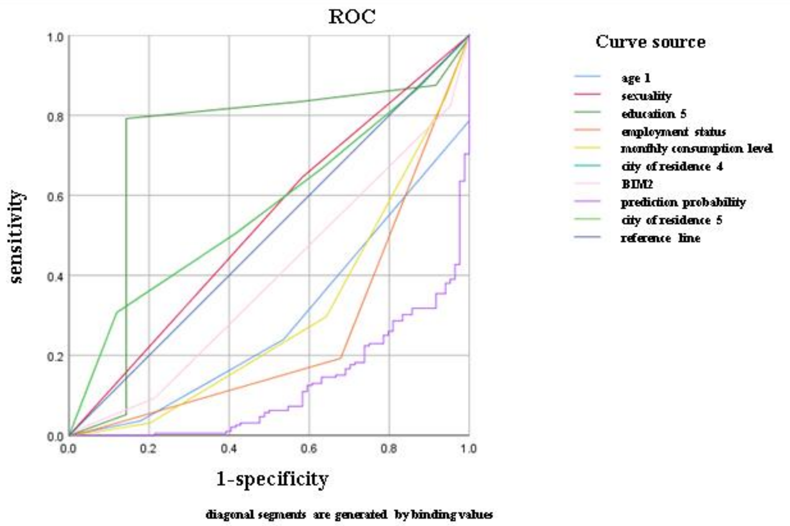

Figure 4 Receiver-Operating Characteristiccurve

Table 11 The Region Table below The Curve

The area below the curve					
Test result variables	Area	STDERR	Significance	Asymptotic 95 % confidence interval	
				Lower bound	Upper bound
Age1	0.291	0.033	0.000	0.227	0.355
Sex	0.531	0.038	0.409	0.457	0.606
Edu5	0.725	0.038	0.000	0.651	0.799
Job1	0.256	0.034	0.000	0.189	0.323
Con 2	0.300	0.035	0.000	0.231	0.369
City4	0.569	0.035	0.068	0.500	0.639
BIM2	0.392	0.036	0.004	0.321	0.463
Prediction probability	0.122	0.021	0.000	0.081	0.162
City5	0.569	0.035	0.068	0.500	0.639

The maximum number of regions below the ROC curve is 0.725, which is greater than 0.7, so the model has greater discrimination (Table 12).

Table 12 Omnibus Test of Model Coefficients

	chi-square	significance
procedure	125.662	0.000
Model Block	125.662	0.000
model	125.662	0.000

Table 13 Hosmer-Lemeshaw Test

procedure	chi-square	degree of freedom	significance
1	12.337	7	0.090

Because R2 is equal to 0.690, the fitting effect is better; the P value of the Omnibus test model was 0.000, less than 0.05. In summary, the Logistic model as a whole is statistically significant. As shown in Table 13, the significance level of the Hosmer-Lemeschau test is equal to 0.090, greater than 0.05. It shows that the information in the data has been fully extracted, there is no significant difference between the predicted value and the observed value, and the model fitting degree is good. As shown in Table 14, the classification prediction accuracy of the Logistic regression model is 72.5 %, the accuracy is high, and the model effect is good.

Table 14 Partial Results of Logistic Test

variable	significance
age	***
sexuality	***
record of formal schooling	***
employment status	***
Monthly consumption level	0.171
City of residence	0.102
BMI value	0.057
*p<0.05 **p<0.01 ***p<0.001	

(1) Significant factors: Age significantly affects young people 's willingness to buy innovative low-fat snacks, and respondents aged 19-23 showed the highest interest. Gender also played a role, as female respondents were twice as likely to buy innovative low-fat snacks than men, possibly due to greater emphasis on diet management. Education is another significant factor, and 63.44 % of the respondents who are willing to buy such snacks are undergraduates, indicating that respondents with bachelor 's degree are more inclined to buy. Employment status significantly affected purchase intention, and students showed the strongest purchase intention, indicating that they prioritized healthy and innovative low-fat snacks.
(2) Non-significant influencing factors: monthly consumption level ($P > 0.05$) had no significant effect on the willingness to purchase innovative low-fat snacks, because consumers were willing to pay a reasonable price for healthy choices after the epidemic[11]. The city of residence ($P > 0.05$) also had no significant effect on purchase intention, which may be due to the common interest in healthy eating in different cities. Height and body mass index (BMI) ($P > 0.05$) were also not significant, because increased awareness of healthy eating weakened its impact on low-fat snack purchase intention.

4.2 Strategy Analysis of Different Customer Groups Based on K-means

4.2.1 K-means crowd clustering
This paper uses the cluster analysis of user response to create consumer portraits, and provides help for the strategic innovation of low-fat snacks for different groups. By simplifying the analysis dimension and enhancing the readability of the results, it lays a foundation for in-depth exploration of different customer segments.
(1) The theoretical basis of crowd classification: K-means algorithm measures the similarity within the group based on the distance from the center of the group. It first selects an initial number of groups (k), and assigns sample points to the nearest center, iteratively updates the center until it reaches stability. This study will also adjust the RFM model that evaluates customer value through recent, frequency and monetary indicators to the LFM model that incorporates Likeness in order to make a more relevant analysis of low-fat snack preferences. The adjusted model helps to identify the value orientation of different customer groups and formulate corresponding marketing strategies. [12]
(2) Variable selection: The analysis considered three variables, preference for low-fat snacks, purchase frequency, and consumption budget. The 'favorability' is measured based on a scale from 'very good' to 'very poor', while the purchase frequency is from 'always' to 'almost no'. The purchase price is evaluated according to the ratio of '21 yuan or more' to '0 ~ 10 yuan'. These variables together assess customer value.
(3) Result analysis: The iterative results of SPSS show that the results after four iterations are stable, so four consumer groups are determined according to the degree of favorability, purchase frequency and price:
Active customers: Advocates of high favorability, frequency and price loyalty of low-fat snacks with significant market value.
Developmental customers: have higher affinity, average frequency and higher price key growth targets because they have strong potential.
Potential customers: generally favorable degree and frequency, low price challenge conversion, but with the potential for improvement.
Silent customers: General favorability, low frequency, low price-high switching costs and low market value, representing the lowest priority of the brand.
The data showed that 52.47 % of the respondents were in favor of low-fat snacks, and the silent customers had the highest approval of low-fat snacks, which was 95.2 %. This shows that there is a huge market potential among young consumers, highlighting the need for brands to transform goodwill into purchase behavior through innovative marketing strategies (Table 15-20).

Table 15 RFM Model Customer Classification Standard Table

customer type	numbering	feature
general value	111	Consumption time is not far, consumption frequency and consumption amount of medium level.
General developing	110	Consumption time is not far, the amount of consumption is general, the frequency is not high, can be excavated.
Generally keep	011	The consumption time is far away, but the consumption frequency and amount are OK, and there is the possibility of awakening.
General retention	001	Consumption time is far away, consumption frequency is not high, have a certain consumption ability, should be given to retain measures.
important values	222	The recent consumption time, consumption frequency and consumption amount are very high.
Important to develop	202	Recent consumption time is close, the amount of consumption is high, but the frequency is not high, loyalty is not high, very potential users, we must focus on development.
Important to maintain	022	The recent consumption time is far away, but the consumption frequency and amount are high, indicating that this is a loyal customer who has not come for a period of time. This study needs to take the initiative to keep in touch with him.

Important Retention	002	Recently, users with long consumption time and low consumption frequency, but high consumption amount, may be users who will be lost or have been lost, and should be given retention measures.

Table 16 Cluster Variable Summary Table

Dependent variable	The questionnaire number and questionnaire questions involved
favorability	8.What is your preference for low-fat snacks?
purchase frequency	9.What is the frequency of your purchase of low-fat snacks?
purchase price	12. Which price range do you prefer to buy low-fat snacks?

Table 17 Cluster Analysis Result

Iteration	Changes in cluster centers			
	1	2	3	4
1	1.805	1.987	1.592	1.113
2	0.826	0.038	0.592	0.000
3	0.207	0.144	0.110	0.283
4	0.179	0.016	0.000	0.567
5	0.000	0.000	0.000	0.000

Table 18 Cluster Analysis Result

Number of cases in each cluster			
cluster		1	107.000
		2	129.000
		3	201.000
		4	31.000
	effectiveness		468.000
	deficiency		0.000

Table 19 Group Categorical Features

Naming	A: active customer	B: developmental customer	C: potential customer	D: silent customers
favorability	high frequency (3 points)	high frequency (3 points)	general frequency (1 point)	general frequency (1 point)
purchase frequency	high frequency (5 points)	general frequency (3 points)	general frequency (3 point)	low frequency (1 point)
fraction	8 points	6 points	4 points	1 point
Number of cases	3	3	16	446

Table 20 The Distribution of Respondents' Preference for Low-Fat Snacks

option	subtotal	proportion
A. very good	95	18.81%
B. good	170	33.66%
C. general	218	43.17%
D. lower	18	3.56%
E. very poor	4	0.79%
This topic effectively fill in the number of people	505	100%

4.2.2 Different types of customers' choice of five innovation strategies

This paper analyzes how consumers' different preferences in taste, marketing, sales, packaging and health concepts affect the purchase decision of low-fat snacks, and puts forward strategic reform suggestions for enterprises to target different types of customers. Figure 5 shows that silent customers prioritize product tastes, marketing methods, sales channels, packaging, and health concepts, making their transition to active customers challenging. On the contrary, active customers show a stronger desire to buy due to their focus on health, which indicates a higher sensitivity to product health. The other two customer types are more emphasis on taste and sales channels, which indicates that they are easier to switch. Therefore, in order to successfully transform customer types, merchants should give priority to diversifying product tastes, expanding sales channels, enhancing online sales, and developing healthier options to retain active customers.

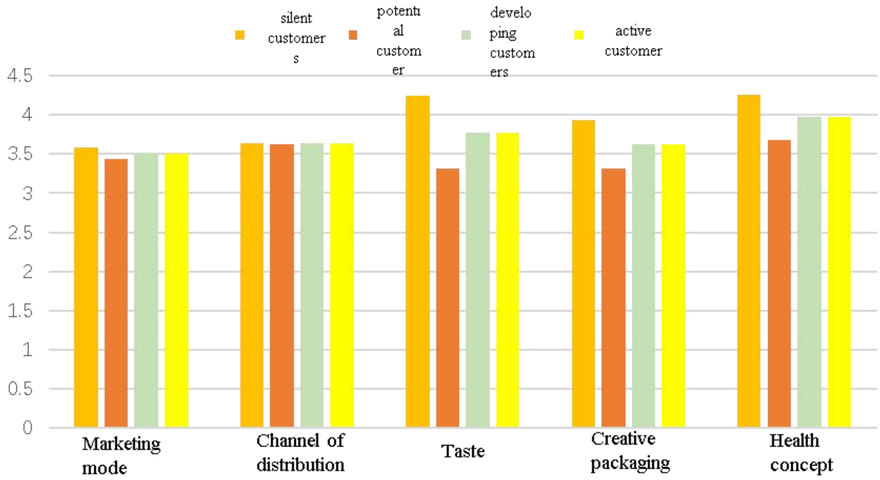

Figure 5 Each type of customer 's score on each innovation strategy (average score)

4.2.3 Preferences of different customer groups for specific ways of each strategy

(1) Innovative marketing ideas

Figure 6 shows that silent, potential and developing customers show a strong interest in sponsoring film and television programs, co-branding with IP, and engaging users in design marketing, reflecting their desire for product awareness and enhanced consumer experience. Active customers also give priority to product awareness, and nearly 100 % of active customers support IP joint marketing. Using well-known online IP for joint marketing can significantly enhance brand influence and sales. Therefore, low-fat snack enterprises should formulate corresponding marketing strategies according to the preferences of different customer groups.

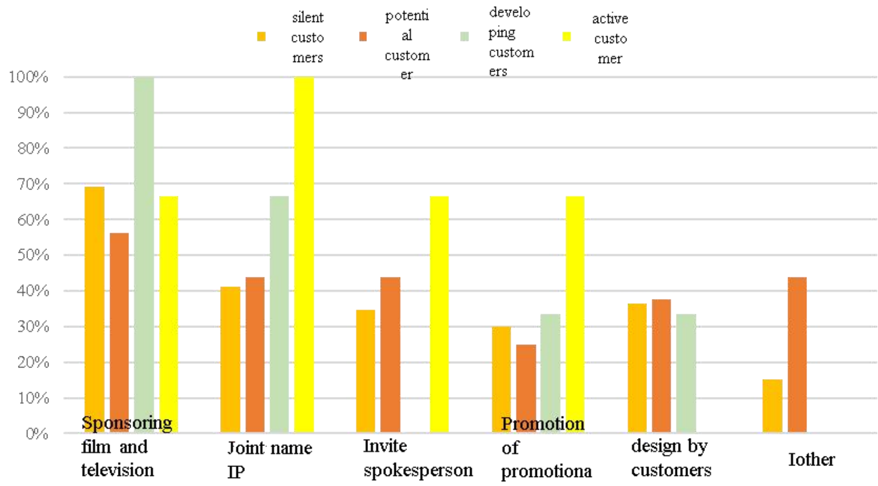

Figure 6 The love of different customer types for different marketing ideas

(2) Sale-channel innovation

Figure 7 shows that silent customers prefer offline experience stores and self-service vending machines, with preferences of 83.4 % and 69.2 % respectively. Potential customers also favor self-service vending machines (62.5 %), while development customers tend to shop online. All three groups seek greater purchase convenience and enhanced shopping experience. Active customers have less change in channel preference, which may be due to their frequent purchases.

Figure 7 The love of different customer types for different sales channels

(3) Product packaging innovation

Figure 8 shows that customers give priority to environmentally friendly packaging, cover design, packaging and logo, indicating a preference for unique and trendy design. Active customers mainly focus on cover design, while other types of customers also value environmental considerations in packaging.

Figure 9 emphasizes that all four customer types give priority to health in low-fat snacks ; for example, 86.54 % of active customers prefer products with low preservative content and rich in healthy ingredients. Given the long shelf life of snacks, consumers expect fewer preservatives, prompting companies to focus on health by developing healthier options.

Figure 10 illustrates the common trend of all customer groups regarding the type and taste of low-fat snacks. For example, developing customers prefer tastes closer to traditional snacks and a wider range of products, which indicates important problems in the current market, such as limited variety and poor taste compared to traditional snacks. In order to compete, low-fat snack companies must diversify their products and invest in new technologies or better fat substitutes to improve taste, as poor flavors seriously hinder consumers' repurchase rates.

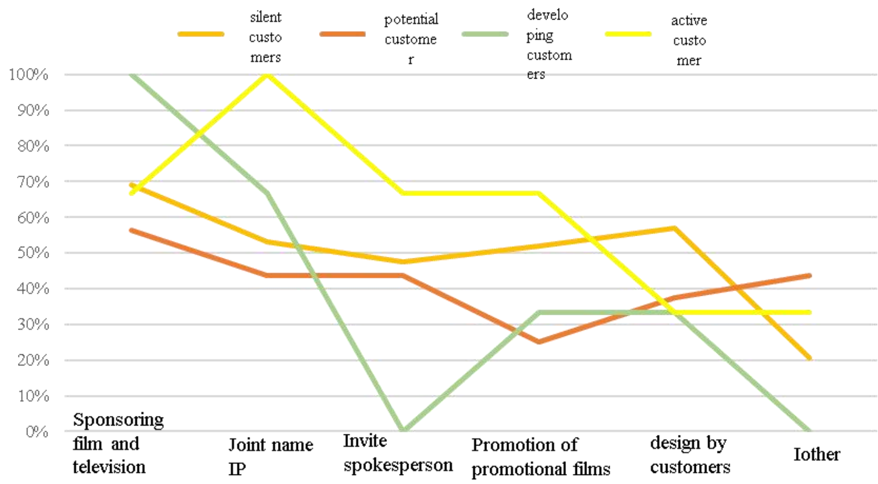

Figure 8 The Preference of Different Customer Types for Different Packaging Innovation Methods

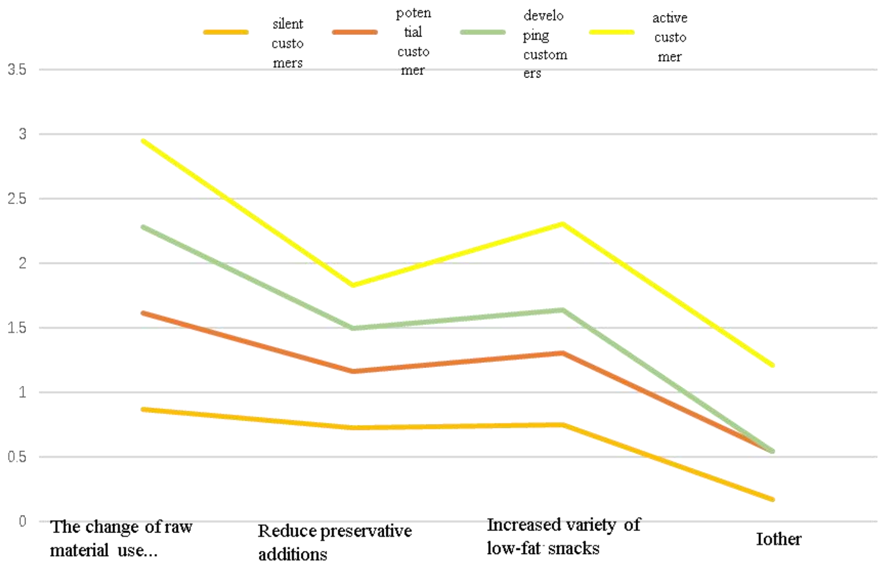

Figure 9 The Preference of Different Customer Types for Different Health Concept Innovation Methods

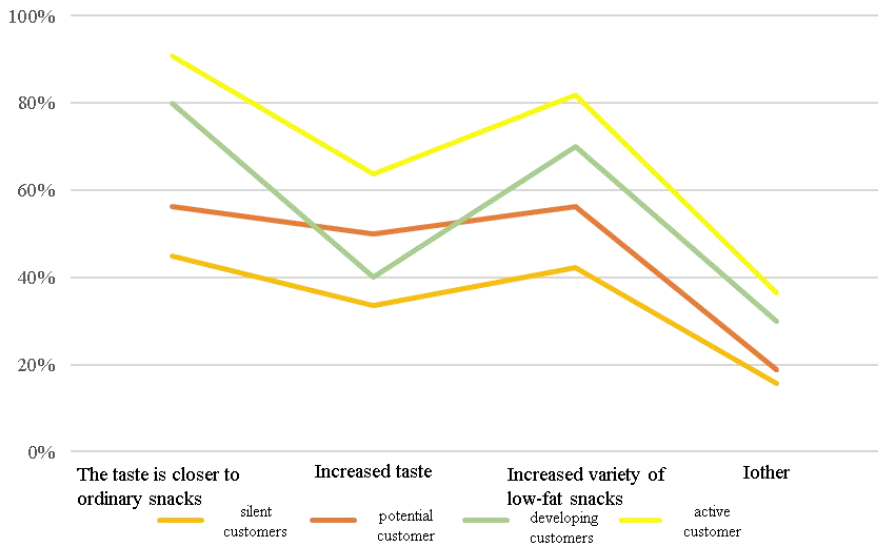

Figure 10 The Preference of Different Customer Types for Different Taste Innovation Methods

5 BASED ON THE NEURAL NETWORK MODEL, THE INFLUENCE OF INNOVATION STRATEGY ON PURCHASE INTENTION IS ANALYZED

5.1 Model overview

The neural network model imitates the structure and function of the human brain to perform tasks such as classification and clustering. It includes input layer, hidden layer and output layer. The input layer receives external data, passes it to the hidden layer for processing, and then passes it to the output layer for prediction. In this study, a multi-layer feedforward neural network with back propagation is used to train the model efficiently[13].

5.2 Modelling

A neural network model was constructed to analyze the influence of 18 specific strategies on the purchase intention of low-fat snacks among young consumers in Guangxi. The dependent variable of the model is the purchase intention, and the independent variable is the improvement strategy. The data is divided into training set and test set for model construction, training, testing and application (Table 11-12).

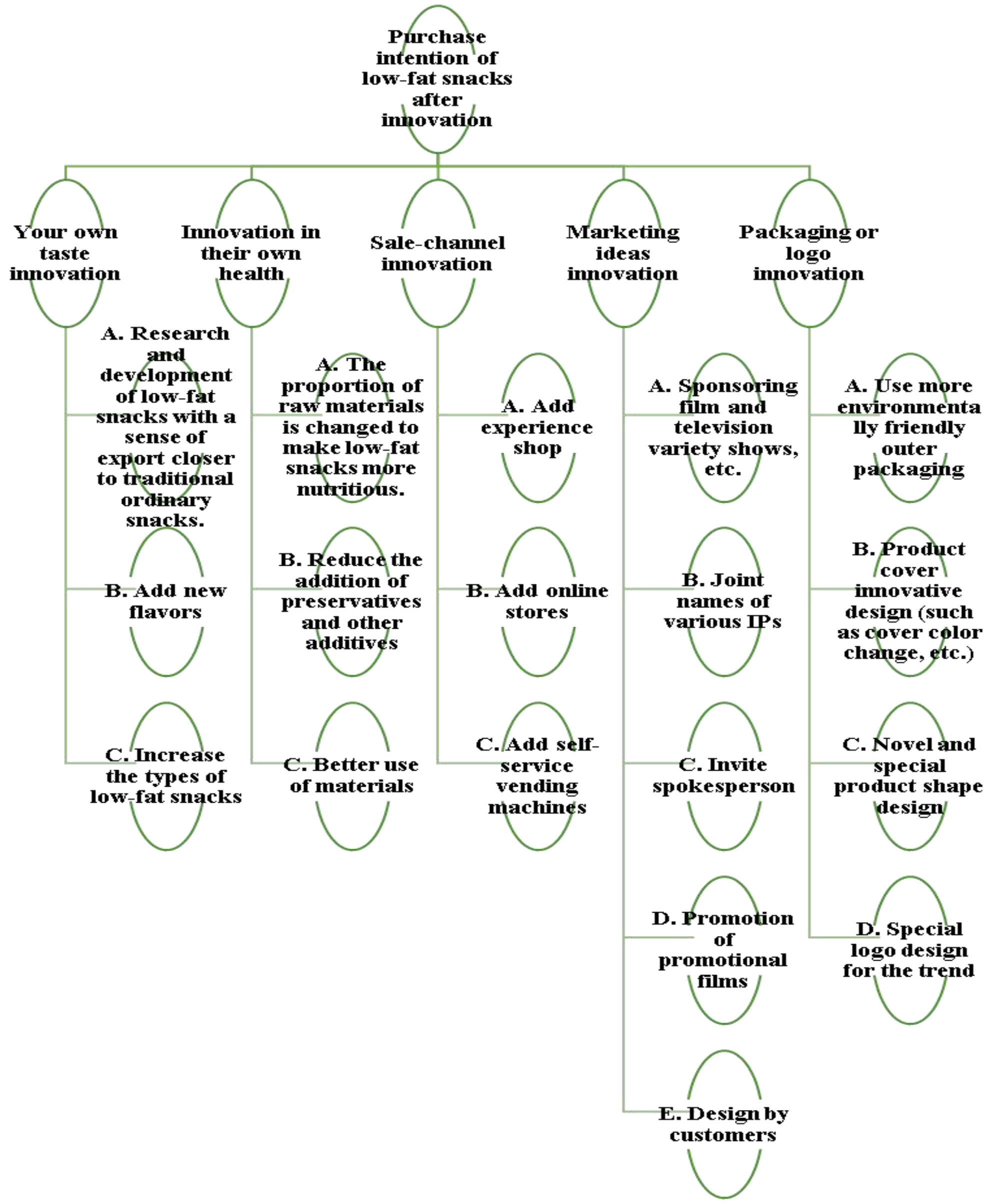

Figure 11 Factors Affecting the Purchase of Innovative Sugar Free Beverages

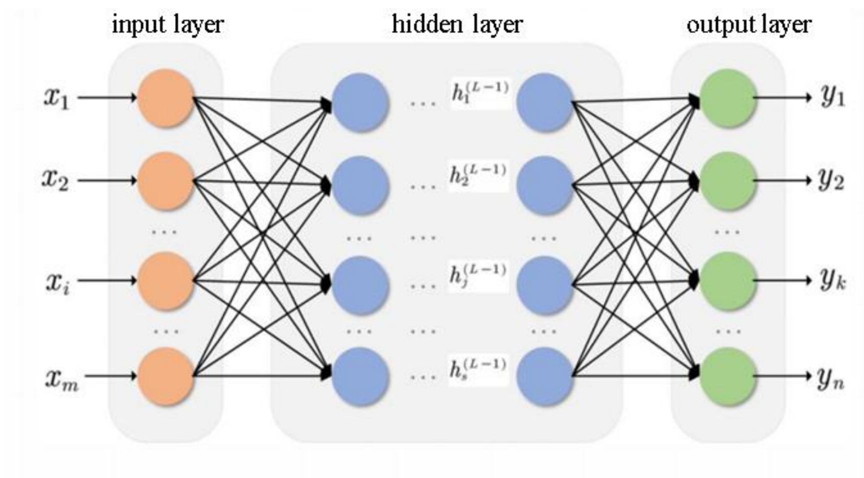

Figure 12 Neural Network Model Structure

5.3 The Influence of Low-Fat Snack Innovation Strategy on Purchase Intention

The importance of different strategies is determined by shuffling feature columns and predicting loss values. It was found that strategies such as 'inviting spokespersons' and 'promoting promotional videos' were found to be more important, which is consistent with the trend-seeking behavior of young consumers (Table 13).

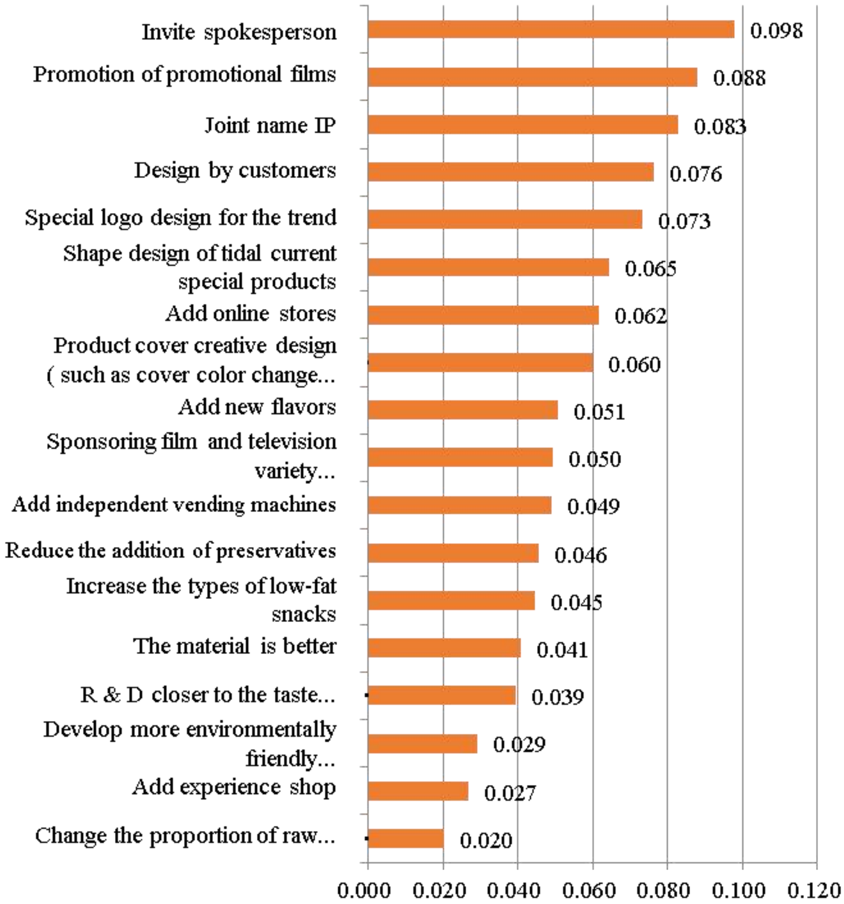

Figure 13 The Order of Importance of Factors Affecting Purchase Intention

6 CONCLUSION AND SUGGESTION

6.1 Conclusion

(1) Enterprise perspective
Online sentiment analysis shows that low-fat snacks are very popular among young consumers, showing growth opportunities under the trend of healthy eating after the COVID-19 epidemic. Although individuals aged 14 to 30 do not often buy these snacks, they are very open to innovative options and show great potential for development[14]. This study also found different innovation strategy preferences among different types of customers, emphasizing that health and taste are essential for retaining active customers and switching silent customers. In addition, logistic regression analysis shows that there are young consumers who are sensitive to the improvement or innovation of low-fat snacks, suggesting that companies should target these preferences to enhance product attractiveness, promote sales, and increase market share.
(2) Consumer perspective
According to the survey, 93.07 % of respondents were willing to buy low-fat snacks with novel packaging, 94.06 % were in favor of innovative marketing ideas, and 88.12 % accepted new concepts. This indicates that young consumers have a strong willingness to purchase innovative low-fat snacks. In addition, in the digital age, young consumers value branded products with cultural significance and attractiveness, emphasizing the importance of influential first impressions. Consistency in the packaging of low-fat snacks currently discourages purchase intention, suggesting that brands should invest in creative packaging design to capture consumer attention and stimulate desire to buy. Finally, all customer types expressed high expectations for the taste and health of low-fat snacks. Given the low profitability and market share of existing brands, coupled with consumer resistance to the health and taste of existing products, it is clear that enhancing these attributes is essential to influence young consumers ' willingness to buy.

6.2 Proposal

6.2.1 Enterprise

1) Technological innovation is the key to maintain the competitiveness of enterprises[15]. Companies should invest in research and development to discover new low-fat ingredients and bioengineered fat substitutes[16], such as apple fiber, to increase health value and control costs, while developing snacks that help fat burn and improve sleep.
2) Taste is very important for consumers ' choice. Enterprises should focus on product development, create a diversified flavor experience by adjusting the formula, use natural flavors and low-calorie sweeteners, and introduce seasonally restricted flavors to stimulate consumer interest.
3) Innovative packaging design is essential to attract consumers ' attention. Enterprises should use environmentally friendly materials and creative logos to convey brand value through packaging stories. In addition, the design should be social media friendly to increase brand awareness.。
4) Strong brand image is an important asset. Enterprises should clarify brand positioning, use public relations and social responsibility initiatives to carry out effective marketing and create a positive image. For brands with negative perception, transparency in dealing with problems helps to rebuild trust.。
5) Collaborative IP and interactive marketing can attract young consumers. Enterprises should cooperate with popular movies and games, provide limited edition products, and use social media to carry out online activities to promote consumer participation.

6.2.2 Government

1) The government should strengthen health education and promote reasonable consumption, especially in students and areas with high incidence of disease. Initiatives like advertising and workshops can raise awareness of low-fat and low-calorie choices, as well as the importance of reading food labels.
2) The government should give incentives such as subsidies and tax breaks to health care products manufacturers, and cultivate a supportive market environment that encourages innovation and fair competition through intellectual property protection and legal construction.
3) Governments should regulate the use of fat substitutes to ensure healthy industrial development and implement policies based on successful international practices to address high fat content in snacks.
4) The government should strengthen market supervision and crack down on false advertising in the field of low-fat snacks. This includes enforcing food safety laws, monitoring advertising claims, and establishing consumer reporting and complaint mechanisms to protect consumer rights and maintain market integrity.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

FUNDING

Funding from the National/Autonomous Region level College Students' Innovation and Entrepreneurship Training Program of Guangxi University for Nationalities; project number: S202410608103.

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3055

THE IMPACT OF DIGITAL MERGERS AND ACQUISITIONS ON TOTAL FACTOR PRODUCTIVITY UNDER THE CULTIVATION OF NEW QUALITY PRODUCTIVITY

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Abstract: In the context of the digital age, the cultivation of new quality productivity has become the key to promoting high-quality economic development.This article aims to explore how digital mergers and acquisitions, under the cultivation of new quality productivity, can increase the number of patents through innovative technologies and innovate business models, thereby affecting the overall factor productivity of enterprises.This study uses digital mergers and acquisitions events of Chinese A-share listed companies from 2015 to 2022 as samples, and uses multiple regression analysis to systematically examine the impact and mechanism of digital mergers and acquisitions on total factor productivity of enterprises.The study found that firstly, digital mergers and acquisitions significantly improved the total factor productivity of enterprises, and this effect gradually emerged and remained stable within two years after the merger.Secondly, through technological synergies, digital mergers and acquisitions have promoted the improvement of corporate innovation capabilities and optimized resource allocation efficiency.In addition, digital mergers and acquisitions enhance the market competitiveness and customer value creation ability of enterprises through innovative business models.Heterogeneity analysis shows that digital mergers and acquisitions of non-state-owned enterprises have a more significant effect on improving their total factor productivity.
This study not only enriches the relevant theories of digital mergers and acquisitions and enterprise productivity, but also provides empirical basis for the government and enterprises to formulate relevant policies and strategies in the process of digital transformation.Future research can further explore the long-term effects of digital mergers and acquisitions and their mechanisms in different industry contexts.
Keywords: Digital mergers and acquisitions; New quality productivity; Total factor productivity

1 INTRODUCTION

The scale of China's digital economy has continued to expand in recent years, with a growth rate significantly higher than the GDP growth rate during the same period. In 2023, the digital economy will account for 42.8% of GDP and contribute 66.45% to GDP growth. The digital economy is gradually developing into an important support for new quality productivity, promoting high-quality economic development through technological innovation and integrated applications.The improvement of total factor productivity in the digital economy is a core indicator of the accelerated formation of new quality productivity.In addition, the digital economy plays an important role in innovation driven, integrated empowerment, and the release of data element value, and is closely connected to other fields.The rapid development of the digital economy has provided strong impetus and technological support for the digital transformation of enterprises, promoting the in-depth development of digital transformation in enterprises.According to data from Light up Think Tank and CITIC Union, as of 2023, 10.15% of enterprises in China have undergone substantial transformation, and nearly 90% of enterprises have focused their digital transformation efforts on achieving standardized business operations and management through information technology applications. According to the "China Small and Medium sized Enterprises Digital Transformation Report 2024", 62.6% of small and medium-sized enterprises are still in the early stages of digitalization, and the digital transformation index level of large enterprises is 40% higher than that of small enterprises [1]. In addition to differences in enterprise size, there are also differences in the digital transformation process between industries.For example, industries such as communication, electronics, and petrochemicals are in the first tier of digital transformation, while industries such as food, building materials, light industry, and construction are relatively lagging behind.In recent years, although digital transformation has been a common trend for enterprises, there are still some problems in the process of combining it with the development of the digital economy.The main focus is on the uneven level of digitalization, insufficient integration of technology and business, insufficient protection of data security and privacy, and high cost of digital transformation. Therefore, it requires joint efforts from the government, enterprises, and all sectors of society to strengthen cooperation and investment in policy guidance, talent cultivation, and other aspects [2]. Digital mergers and acquisitions are an important way for enterprises to gain technological advantages and achieve transformation and upgrading in the digital economy era. For example, Wentai Technology adopted a "two-step" transaction approach and successfully acquired control of Anshi Semiconductor. After the merger, Wentai Technology accelerated its layout and expansion in emerging markets by leveraging its advanced technology and management experience. Through mergers and acquisitions, it effectively integrated upstream and downstream resources in the semiconductor industry chain, optimized resource allocation, more efficiently utilized production factors, improved production efficiency and product quality, and thus enhanced overall productivity.Compared with 2015, in 2018, Wentai Technology saw a 53.65% decrease in asset investment and a 1281.46% increase in human resources investment. However, its operating revenue and profit increased by 2321.07% and 149.10% respectively. Its output growth rate was much higher than the input growth rate, and the company's total factor productivity significantly improved [3].

The new quality productivity is marked by the improvement of total factor productivity, and the core is innovation.In the context of the digital economy, the new quality productivity takes scientific and technological innovation as the essence of promoting industrial innovation, and takes the substantial improvement of total factor productivity as the goal. It strengthens the integration and application of digital technologies such as artificial intelligence, big data, the Internet of Things, and the industrial Internet, and uses data development and utilization as the engine to promote the innovative allocation of production factors, and promote the birth of new industries, new models, and new drivers.In the new industrial system, the industrial format model is constantly updated and developed, and the industrial chain is gradually expanding [4]. New quality productivity, with technological innovation as its core, provides a technological foundation and driving force for digital mergers and acquisitions, while also providing direction for the improvement of total factor productivity.In terms of theoretical research on "new quality productivity", current studies mainly focus on philosophical and political economic perspectives as well as mainstream economic theories. From the perspective of Marxist materialist conception of history, starting from the perspective of "productivity production relations", combined with the actual development of China's industrial economy, it is believed that the essence of developing new quality productivity is a qualitative change in economic development, with the core being to improve total factor productivity [5]. Furthermore, from the perspective of evolutionary economics, knowledge production and diffusion have been the endogenous driving forces behind the development of new quality productive forces since the Industrial Revolution.Among them, the collaborative evolution of technological systems and organizations plays a very important role.In terms of practical application, new quality productivity has been explored in areas such as technological equipment innovation, vocational education services, and international trade rules, but there is relatively little research on digital mergers and acquisitions.

- Digital M&A refers to a strategic choice for enterprises to use digital technology and platform economy mode to promote digital transformation of enterprises and enhance their competitiveness and innovation ability through acquisition, merger or equity investment. The rise of the Internet economy has broken the traditional industrial boundaries and promoted digital transformation and innovation in all walks of life.Traditional enterprises are facing enormous competitive pressure, while also gaining opportunities for digital mergers and acquisitions.By acquiring or investing in Internet enterprises, traditional enterprises can quickly acquire new markets, new channels and new technologies, and accelerate the process of digital transformation [6].In the process of digital transformation, enterprises need to continuously acquire advanced digital technologies and talents, and digital mergers and acquisitions have become an important means for enterprises to achieve digital transformation and enhance competitiveness.The role of digital mergers and acquisitions in cultivating new quality productivity is mainly manifested in five aspects, namely technology acquisition and innovation, market expansion and channel optimization, talent and resource aggregation, corporate culture and strategic synergy, and promoting industrial transformation and upgrading.Regarding digital mergers and acquisitions, through relevant research on digital mergers and acquisitions, many studies have mainly focused on its effect mechanisms, driving trends, merger models, and strategies, reflecting the important position of digital mergers and acquisitions in digital economic activities.From the perspective of research on the impact of digital mergers and acquisitions, existing studies have explored its effects on corporate performance, digital transformation, innovation performance, and digital platform economic performance. Digital mergers and acquisitions provide data support for improving corporate innovation performance and promoting digital transformation.There is relatively little research on the impact of digital mergers and acquisitions on total factor productivity, and most of it focuses on the theoretical level.In November 2024, Guotai Junan and Haitong Securities announced their merger and reorganization, which received approval from the Shanghai State owned Assets Supervision and Administration Commission, and released a draft merger and reorganization report.Both companies are leading securities firms in China, and the merger will form an investment bank with stronger capital strength.The capital strength of the newly merged company has significantly increased, with both net assets and net capital ranking first in the industry.Stronger capital strength will significantly enhance the risk tolerance of the merged company, improve capital utilization efficiency and fund utilization effectiveness.At the same time, both companies will establish new corporate governance structures, management structures, development strategies, and corporate cultures to promote effective business integration and enhance overall profitability. These changes are expected to drive the improvement of total factor productivity.

At present, domestic and foreign scholars' research on digital mergers and acquisitions mainly focuses on their motives and performance, and has added some new theories for analysis.In foreign research, the main direction of motivation research is the Ecological Environment Specific Advantage Theory (ESA) and externalization logic. ESA theory believes that the motivation for mergers and acquisitions of digital enterprises is not only to save transaction costs, but also to acquire and utilize external resources to maintain ecological environment advantages. The study of externalization logic refers to the tendency of digital enterprises to acquire external resources through mergers and acquisitions.In terms of performance research, foreign scholars have analyzed the performance of digital mergers and acquisitions through methods such as case studies and event study.Some studies have found that digital mergers and acquisitions can improve corporate performance, especially in the short term;But there are also some studies indicating that it may bring certain risks and uncertainties, which require companies to carefully evaluate.

In the study of the driving forces behind digital mergers and acquisitions in China, it has been found that the main reasons are due to the demand of traditional enterprises for digital transformation, market expansion, and resource integration. In addition, domestic scholars have used methods such as principal component analysis, event study, and factor analysis to study the performance of digital mergers and acquisitions. They have also found that digital mergers and acquisitions can improve corporate performance or pose risks in the medium to long term.It can be seen that there is still limited research on the impact of digital mergers and acquisitions on total factor productivity.

The factors that affect total factor productivity are complex and diverse, and existing research has mainly explored them from the aspects of financial development level, technological innovation, labor market, etc.Total factor productivity is an important indicator for measuring the quality and efficiency of economic development, reflecting the comprehensive utilization efficiency of various input factors in the production process.Improving total factor productivity is an important way to enhance the efficiency of resource allocation in state-owned enterprises and promote their high-quality development.Ouyang Zhigang et al. explored the issue of resource allocation and total factor productivity from the perspective of debt finance based on the realistic background of financial resource allocation in China's manufacturing industry, and analyzed the relationship between different types of enterprises [7].TFP, as a key indicator for measuring the production efficiency of enterprises, its improvement is the core for enterprises to achieve sustainable development and enhance market competitiveness.There is a close relationship between new quality productivity, digital mergers and acquisitions, and total factor productivity.New quality productivity, with technological innovation as its core, provides a technological foundation and driving force for digital mergers and acquisitions, while also providing direction for the improvement of total factor productivity.Digital mergers and acquisitions, as a way for companies to expand, promote innovation and development by acquiring new technologies, increasing market share, and other motivations. They provide a pathway for companies to innovate their business models, thereby improving total factor productivity.The improvement of total factor productivity, in turn, provides an economic foundation and driving force for the development of new quality productivity.

This study first analyzed the connotation of digital mergers and acquisitions and the current research status of digital mergers and acquisitions at home and abroad, and then systematically sorted out the theories and literature on the relationship between digital mergers and acquisitions and TFP.On the basis of this theoretical construction, this article proposes research hypotheses, using digital merger and acquisition events of Chinese A-share listed companies from 2015 to 2022 as samples, designing a benchmark regression model to study the linear relationship between independent and dependent variables, and finally, using panel data regression analysis method to conduct in-depth research and testing.

The research contribution of this article mainly lies in its theoretical and practical significance.

In terms of theoretical contribution, it is mainly reflected in the enrichment and development of productivity theory on digital mergers and acquisitions under the new quality productivity, deepening the research on types of corporate mergers and acquisitions, and expanding the theory of total factor productivity.

Firstly, although research has confirmed that digital mergers and acquisitions have a promoting effect on total factor productivity of enterprises, most of these studies focus on the synergies and human capital effects brought about by digital mergers and acquisitions.Liu Weilin et al. explored the network effects of total factor productivity growth and transmission measurement based on the global production network, reflecting the total factor productivity growth and spillover effects at the national and industrial levels under the dual circulation condition [8].This article incorporates technological innovation and business model innovation into the analytical framework, further refining the impact path of digital mergers and acquisitions on total factor productivity of enterprises, and enriching the research content in this field.

Secondly, traditional research on corporate mergers and acquisitions mainly focuses on technology mergers and acquisitions, green mergers and acquisitions, and other aspects, while there is relatively little research on corporate mergers and acquisitions behavior from the perspective of digital technology.This article takes digital mergers and acquisitions as the research object, exploring their mechanism in improving the total factor productivity of enterprises, which helps to expand the relevant research on the types of corporate mergers and acquisitions from the perspective of digital technology.

Thirdly, total factor productivity is an important indicator for measuring economic growth efficiency and technological progress, and its influencing factors are complex and diverse.This article incorporates digital mergers and acquisitions into the analytical framework, exploring their impact on total factor productivity from the perspectives of technological and business model innovation. This will help enrich the research on factors affecting productivity and provide a new theoretical perspective for improving enterprise production efficiency.

In practical terms, the research on the impact of digital mergers and acquisitions on total factor productivity under the new quality productivity mainly reflects three aspects: guiding the digital transformation of enterprises, optimizing resource allocation efficiency, and providing scientific basis for policy systems.

- Firstly, this study is of great significance in guiding the digital transformation of enterprises.By revealing the role of digital mergers and acquisitions in improving total factor productivity, this study provides an effective way for companies to acquire digital technologies and services through mergers and acquisitions, build digital capabilities, and enhance competitive advantage and corporate performance.This helps companies better adapt to the development environment of the digital economy and achieve efficient and sustainable development.

Secondly, by analyzing the impact mechanism of digital mergers and acquisitions on total factor productivity, the research results of this article help enterprises recognize the role of digital mergers and acquisitions in optimizing resource allocation and improving economic efficiency, thus enabling more scientific resource allocation and production management.

Thirdly, this study has important reference value for the government to formulate relevant policies.New quality productivity is a productivity leap caused by a new round of technological revolution represented by intelligent and green technologies, characterized by disruptive innovation driven, fast development speed, and high development quality.By enhancing total factor productivity through digital mergers and acquisitions, the government can encourage digital M&A activities by introducing relevant policies, and strengthen supervision and guidance of digital M&A activities to ensure their healthy development.

2 THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

There are some key differences between traditional digital mergers and acquisitions and digital mergers and acquisitions under the cultivation of new quality productivity in terms of goals, processes, and outcomes.In terms of target differentiation, traditional digital mergers and acquisitions typically focus on acquiring specific digital assets, technologies, or user bases to enhance existing businesses or enter new markets, with the goal of achieving short-term financial gains and increasing market share.Under the cultivation of new quality productivity, digital mergers and acquisitions tend to promote long-term technological innovation and productivity development through mergers and acquisitions. The goal of cultivating new quality productivity includes not only financial returns, but also enhancing the core competitiveness, innovation capability, and sustainable development capability of enterprises.In terms of process differences, Traditional digital mergers and acquisitions may focus more on short-term improvements in financial and market performance, while post merger integration may primarily focus on cost savings and revenue growth. In contrast, the overall process of digital mergers and acquisitions under the cultivation of new quality productivity tends to emphasize the integration of technology and innovation capabilities, as well as long-term R&D investment, talent cultivation, and innovation culture construction.Overall, as an important form for enterprises to acquire digital technology in the digital economy era, digital mergers and acquisitions have stronger digital technology requirements compared to traditional mergers and acquisitions. Enterprises hope to directly acquire new technological resources through mergers and acquisitions, reduce their own research and innovation risks, and accelerate digital transformation.Under the cultivation of new quality productivity, digital mergers and acquisitions pay more attention to long-term technological innovation and productivity development, while traditional digital mergers and acquisitions may focus more on short-term financial and market goals.Under the cultivation of new quality productivity, enterprises not only acquire technology and market resources through digital mergers and acquisitions, but also achieve sustainable competitiveness enhancement through integration and innovation.Research hypothesis 1: Digital mergers and acquisitions can effectively improve total factor productivity

Digital M&A refers to the merger and acquisition activities of companies in order to acquire digital technology, talent, data assets, or other related resources.This type of merger and acquisition activity is becoming increasingly important in the context of digital transformation and digital economy.Total factor productivity (TFP) refers to the rate at which output increases while the input of all production factors (such as labor, labor capital, land, etc.) remains constant. It is influenced by technological progress, human capital, resource allocation efficiency, and economies of scale.It reflects the comprehensive utilization efficiency of production factors, the optimization of production methods, and the progress of production technology.Changes in production relations, such as property rights and distribution systems, can affect the improvement of TFP.Digital mergers and acquisitions promote enterprise efficiency and innovation capabilities by increasing total factor productivity (TFP). Digital mergers and acquisitions can enable enterprises to quickly acquire advanced technology and management experience, promote technological integration and innovation, and thus improve production efficiency and product quality.In terms of the mechanism of action, Huang Bo et al. found in their research that participating in strategic alliances can enhance the total factor productivity of enterprises and is positively correlated with the strength of strategic partners [9].Secondly, the talent integration and skill enhancement brought about by mergers and acquisitions can help improve employees' productivity and innovation capabilities, especially when the two parties have complementarity in technology and management.Furthermore, digital mergers and acquisitions can drive companies to explore new business models, such as platform based economies, subscription services, etc., which often have higher operational efficiency and customer value.Although digital mergers and acquisitions may bring integration costs and uncertainties in the short term, in the long run, they help companies build sustained competitive advantages and achieve sustained improvement in TFP.Liu Zhibiao and Ling Yonghui reflected in their research that the service-oriented trend of industrial structure is more obvious, and put forward suggestions to pay attention to supply side structural reform [10].

Research hypothesis 2: Digital mergers and acquisitions improve total factor productivity through technological innovation and business model innovation.

3 RESEARCH DESIGN

3.1 Data Sources

The research sample of this article is Chinese A-share listed companies from 2015 to 2022.The digital M&A data used in this article was compiled from the CSMAR database, and relevant literature was referenced to select all digital economy industry enterprises as the target companies for digital M&A.Due to the fact that the main business of enterprises in the digital economy industry relies entirely on digital technology and digital elements, this article will recognize the following two conditions as digital mergers and acquisitions: firstly, the target enterprise belongs to all the core industries of the digital economy in the Statistical Classification of Digital Economy and Its Core Industries (2021);Secondly, the acquiring company explicitly mentions business transformation or expansion related to digital technology in the merger and acquisition announcement.By filtering the merger and acquisition events in the CSMAR database, the merger and acquisition event data is sourced from the merger and acquisition module in the CSMAR database, including detailed information about the merger and acquisition events such as merger type, transaction amount, transaction date, etc. The financial data of the enterprise is sourced from the CSMAR China listed company financial annual report database, including indicators such as net profit, total assets, and asset liability ratio.

Organize the merger and acquisition information of enterprises from 2015 to 2022 from the Guotai An listed company merger and acquisition database, and then unify the merger and acquisition information into a dataset of "listed companies - year - merger and acquisition scale". Then match this data with the total factor productivity of each listed company.And the original data was screened: 1. Retain the sample of listed companies as merger and acquisition enterprises;2. Delete the sample of M&A companies in the financial industry, whose business models differ significantly from other industries, and whose M&A activities may involve complex financial operations, which are not closely related to the impact of digital M&A on total factor productivity studied in this article. Therefore, they are excluded;3. Exclude ST and ST * sample companies. Due to the unstable financial situation of ST (special treatment) and PT (delisting risk warning) companies, which may cause significant interference with the research results, they are excluded.In addition, to ensure the integrity and reliability of data, listed companies with severe missing financial data, merger and acquisition data, or digital transformation data have been excluded.To eliminate the mixed effects caused by multiple digital mergers and acquisitions during the research period, this article excluded samples of repeated digital mergers and acquisitions to focus on the impact of digital mergers and acquisitions on enterprises themselves.After the above processing, 2069 observation values were finally obtained.

3.2 Variable Definition

3.2.1 Dependent variable

The dependent variable is the total factor productivity (TFP) of the enterprise.In benchmark testing, this article mainly uses five methods to measure the total factor productivity of enterprises, which are calculated by OP, LP, OLS, FE, and GM.

3.2.2 Independent variables

The independent variable is Digital Mergers and Acquisitions (DMA).Digital M&A: Referring to the research results of Hanelt A, Wang Xincheng, Chen Qingjiang, VialG, etc., this article constructs a keyword vocabulary for digital technology applications (see Table 1), and searches and reads the overview of M&A events through keywords to determine whether the M&A is a digital M&A.If enterprise i experiences a digital merger event in year t, the variable is assigned a value of 1; otherwise, it is assigned a value of 0.

Table 1 Keyword List for Digital Technology

1	Digitization, digital resources, digital assets, digital technologies, digital platforms, digital transformation
2	Intelligence, artificial intelligence, intelligence, intelligent manufacturing, intelligent planning, intelligent optimization, intelligent Q&A
3	Information technology, informatization, networking, Internet, Internet of Things, big data, 5G
4	Cloud computing, cloud storage, cloud platform
5	Automatic reasoning, OCR, machine learning, machine vision, machine translation, deep learning, robot, voice recognition, picture recognition, image recognition, neural network, text capture, text recognition, text reading, expert system, learning algorithm, augmented reality, virtual reality, virtual community, blockchain, UAV, nanotechnology, edge computing, mobile computing, quantum computing, quantum technology, 3D printing, e-commerce

3.2.3 Control variables

This article incorporates the following control variables in empirical analysis: company size (Size), company age (Age), proportion of independent directors (IndepDir), profitability (Profit), debt to liability ratio (DebtRatio), and ownership structure (Ownership).

Virtual variables have two aspects: industry and year, see Table 2.

Table 2 Variable definitions and calculation methods

Variable	Variable abbreviation	Variable Definition
Digital mergers and acquisitions	DMA	Is it a digital merger? If a digital merger occurs, it is 1; otherwise, it is 0
Total factor productivity	TFP_OP	Total factor productivity of enterprises measured by OP method
	TFP_LP	Enterprise Total Factor Productivity Calculated by LP Method
	TFP_OLS	Total Factor Productivity Calculated by Least Squares OLS Method

	TFP_FE	Total factor productivity measured within the framework of fixed effects models
company size	Size	According to the total assets of the acquiring party at the end of the period
Company Age	Age	Year of establishment of the acquiring party
Proportion of independent directors	IndepDir	The number of independent directors as a percentage of the board of directors
PROFITABILITY	Profit	Net profit of the acquiring party, total assets at the end of the period
Asset liability ratio	DebtRatio	Closing liabilities of the acquiring party
ownership	Ownership	Determine whether the acquirer is a state-owned enterprise or a non-state-owned enterprise
industry	Industry	The industry classification to which the company belongs is usually based on standard industry classification codes
year	Year	Refers to the specific year of data collection or analysis
Number of patents	Patents	The number of patent authorizations obtained by a company during a certain period of time
operating revenue	Revenue	The income generated by the enterprise in its business activities

3.3 Model Setting

Based on the data of A-share listed companies from 2015 to 2022, a panel data model is first constructed to analyze the impact of digital mergers and acquisitions on total factor productivity.Total factor productivity (TFP) can be measured using different methods such as OP, LP, or ACF.Innovation capability can be measured by indicators such as the number of patent applications and the proportion of research and development expenditures.Business model innovation can be measured through indicators such as new product development, market entry, and revenue model innovation.
The model settings are as follows:
$TFP_{it}=\beta_0+\beta_1 DigitalMergers_{it}+\beta_2 HumanCapital_{it}+\beta_3 Innovation_{it}+\beta_4 \quad BusinessModel_{it}+\gamma X_{it}+\mu_i+\lambda_t+\epsilon_{it}$
Among them, TFPit represents the total factor productivity of the i-th enterprise in the t-th year;DigitalMergersit represents whether the i-th company conducted a digital merger in the t-th year;Human Capitalit represents the human capital level of the i-th enterprise in the t-th year;Innovatoite represents the innovation capability of the i-th enterprise in the t-th year.BusinessModelit represents the level of business model innovation of the i-th enterprise in the t-th year.Xit represents control variables, including enterprise size, age, capital intensity, etc.μ i represents the fixed effect of the enterprise.λ t represents the time fixed effect.ϵ it represents the random error term.

4 EMPIRICAL RESULTS TESTING

4.1 Descriptive statistical results

Table 3 presents the descriptive statistical results of the main variables.From the table, it can be seen that the average of digital mergers and acquisitions (DMA) is 0.101, and the average value is 0.000, indicating that 10.1% of companies engage in digital mergers and acquisitions. Therefore, studying the impact of digital mergers and acquisitions on total factor productivity of companies is of great significance.The mean (median) of total factor productivity (TFP_LP) calculated by LP method is 9.035;The mean (median) of total factor productivity (TFP_OP) calculated using the OP method is 7.110;The mean (median) of total factor productivity (TFP_OLS) calculated using the OLS method is 11.406.

Table 3 Descriptive statistical results of main variables

Indicator Name	N	MEAN	SD	MIN	25th percentile	50th percentile	75th percentile	MAX
TFP_OP	2065	7.017865	1.055778	3.911127	6.326166	6.929331	7.639118	11.41969
TFP_LP	2065	8.731125	1.252085	4.84907	7.918516	8.668736	9.49518	12.95311
TFP_OLS	2065	11.06033	1.459659	6.62013	10.12854	10.97223	11.98168	15.06939
DMA	2065	0.3491525	0.4768177	0	0	0	1	1
company size	2065	22.87659	1.478833	17.6413	21.94906	22.83344	23.70564	28.29301
Company Age	2065	24.83293	5.167231	6	21	24	28	44
independent director	2065	0.3762357	0.0592629	0.25	0.3333333	0.3636364	0.4285714	0.7142857
ln_NP	2065	19.26017	1.592186	13.38976	18.39399	19.26017	20.1597	24.38354
Total assets at the end of the period	2065	22.87659	1.478833	17.6413	21.94906	22.83344	23.70564	28.29301

Indicator Name	N	MEAN	SD	MIN	25th percentile	50th percentile	75th percentile	MAX
Asset liability ratio	2065	55.04851	75.14224	2.8195	37.2875	53.6812	67.6899	3146.67

4.2 Analysis of Benchmark Regression Model Results

Table 4 mainly presents the benchmark regression test results of digital mergers and acquisitions (DMA) and total factor productivity (TFP) of enterprises.This article conducted benchmark regression to verify hypothesis 1, including panel regression and panel regression with control variables added. The regression analysis results are shown in the table.The regression coefficient between Digital Mergers and Acquisitions (DMA) and Total Factor Productivity (TFP_OP) using the OP method is 0.197, and there is a significant positive correlation at the 1% statistical level, indicating that digital mergers and acquisitions have a positive impact on total factor productivity;After adding control variables, there was still a significant positive correlation at the 1% level, and the goodness of fit (R-squared) increased from 2% to 11%, indicating that the relationship became more significant after adding control variables.

Table 4 Benchmark Regression Analysis

	(1) TFP_OP	(2) TFP_OP
DMA	0.197^{***}	0.183^{***}
	(4.57)	(4.34)
age		0.000460
		(1.00)
NP		$5.65e-11^{***}$
		(8.80)
lev		0.000136
		(0.85)
_cons	6.914^{***}	6.862^{***}
	(151.51)	(142.18)
N	2069	2069
df_m	1	3
r2	0.02	0.11

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Collinearity Analysis

Table 5 shows that the VIF values of each variable do not exceed 10, and the mean VIF value also does not exceed 10, so there is no collinearity.

Table 5 Results of collinearity analysis

variable	VIF	1/VIF
DMA	1.01	0.98
NP	1.01	0.99
Lev	1	0.99
Age	1	0.99
Mean VIF	1.01	

5 MECHANISM TESTING

5.1 Technical Synergy Effect

The technological synergy effect is mainly reflected in the overall technological innovation capability of the enterprise group, forming technology and knowledge spillover effects within the enterprise.This article uses the Enterprise Innovation Capability (PATENT) to measure the technological synergy effect, defined as the logarithm of the number of patent applications plus one.

Table 6 presents the mechanism test results of technological synergy effects. Column (1) shows the regression results between digital mergers and acquisitions (DMA) and total factor productivity (TFP_OP) using the OP method, with a significant positive correlation at the 1% level and a coefficient of 0.183;The second column shows the regression results of the second step of the three-step mediation effect, where the impact of digital mergers and acquisitions (DMA) on the number of patents and inventions of a company is significantly positively correlated at the 1% level;The third column shows the estimation results of total factor productivity (TFP_OP) and the number of company patents and inventions (patents) for digital mergers and acquisitions (DMA) using the OP method. Both digital mergers and acquisitions and the number of company patents and inventions have a significant impact on total factor productivity, with a significant positive correlation at the 1% level.

Combining (1), (2), and (3), it can be found that digital mergers and acquisitions have a significant impact on total factor productivity, and the impact of corporate innovation capability on total factor productivity is significantly positively correlated at the 1% level. From the results, it can be seen that the mediating effect holds true;Digital mergers and acquisitions have improved total factor productivity by enhancing corporate innovation capabilities.

Table 6 Testing of the Effect of Technical Collaboration Mechanism

	(1) TFP_OP	(2) patent	(3) TFP_OP
DMA	0.183^{***}	0.344^{***}	0.143^{***}
	(4.34)	(5.94)	(3.40)
patent			0.0834^{***}
			(7.12)
age	0.000460	0.00445^{***}	0.000511
	(1.00)	(3.02)	(1.13)
NP	$5.65e-11^{***}$	2.60e-12	$5.34e-11^{***}$
	(8.80)	(0.30)	(8.38)
lev	0.000136	0.000105	0.000127
	(0.85)	(0.51)	(0.80)
_cons	6.862^{***}	2.789^{***}	6.622^{***}
	(142.18)	(18.57)	(113.57)
N	2069	2069	2069
df_m	3	3	4
r2	0.11	0.03	0.09

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Innovative Enterprise Business Models

The business model of innovative enterprises can mainly be reflected through indicators such as sales and marketing, operations and management, product and service innovation, technology and digital applications, and financial performance.This article considers using financial performance related indicators to measure the impact of innovative business models on total factor productivity in enterprises. The preliminary proposal is to use the enterprise's revenue growth rate as an indicator, and the financial statement data of the enterprise can reflect the growth of revenue.After digital mergers and acquisitions, if a company's revenue continues to grow and the growth rate is higher than the industry average, it indicates that the new business model has a positive driving effect on the company's business development and can improve its profitability.

Table 7 shows the test results of innovative business models. The regression results between digital mergers and acquisitions (DMA) and total factor productivity (TFP_OP) using the OP method in column (1) show a significant positive correlation at the 1% level, with a coefficient of 0.183;The second column shows the regression results of the second step of the three-step mediation effect, where the impact of digital mergers and acquisitions (DMA) on company marketing expenses (OpEx) is significantly positively correlated at the 1% level;The third column shows the estimation results of total factor productivity (TFP_OP) and company marketing expenses (OpEx) using digital mergers and acquisitions (DMA) and OP method. Both digital mergers and acquisitions and company marketing expenses have a significant impact on total factor productivity, with a significant positive correlation at the 1% level.

Combining (1), (2), and (3), it can be concluded that digital mergers and acquisitions have a significant impact on total factor productivity, and the impact of company marketing on total factor productivity is significantly positively correlated at the 1% level. From the results, it can be seen that the mediating effect holds true;Digital mergers and acquisitions have improved total factor productivity through innovative business models, which is consistent with the expectations mentioned earlier.

Table 7 Results of Testing the Mechanism of Innovative Business Models

	(1) TFP_OP	(2) OpEx	(3) TFP_OP
DMA	0.183^{***}	188287644^{***}	0.163^{***}
	(4.34)	(3.10)	(3.90)
OpEx			$1.13e-10^{***}$
			(7.39)
age	0.000460	-43294.2	0.000464
	(1.00)	(-0.07)	(1.02)
NP	$5.65e-11^{***}$	0.151^{***}	$4.01e-11^{***}$
	(8.80)	(16.36)	(5.97)
lev	0.000136	248400.3	0.000109
	(0.85)	(1.07)	(0.69)
_cons	6.862^{***}	404834031^{***}	6.816^{***}
	(142.18)	(6.09)	(141.63)
N	2069	2069	2069

df_m	3	4	3
r2	0.11	0.56	0.12

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 HETEROGENEITY TEST

6.1 Property Rights Nature

There are certain differences between state-owned enterprises and non-state-owned enterprises in decision-making mechanisms and goal orientation, resource acquisition and utilization capabilities, risk tolerance, and innovation motivation. The impact of digital transformation on the promotion of total factor productivity is very evident in both non-state-owned and state-owned enterprises [11]. State owned enterprises usually bear more social responsibilities, so decision-making in digital mergers and acquisitions requires multiple levels of approval and examination. They may be more inclined to choose target enterprises that are in line with the national development strategy and have important industrial support roles, in order to achieve optimal resource allocation in the industry.For non-state-owned enterprises, decision-making is relatively flexible, mainly guided by market demand and the company's own development, pursuing maximum profit.Secondly, state-owned enterprises have a relatively stable operating environment and can bear a certain degree of risk, while non-state-owned enterprises have relatively weaker risk tolerance.

Table 8 presents the heterogeneity test results regarding the nature of property rights.There is a significant positive correlation at the 1% level for non-state-owned enterprises and at the 10% level for state-owned enterprises, indicating that digital mergers and acquisitions in non-state-owned enterprises have a more significant effect on improving their total factor productivity.Non state-owned enterprises (non-state-owned enterprises) place greater emphasis on improving total factor productivity through digital mergers and acquisitions. This may be due to the fact that non-state-owned enterprises tend to focus more on market responsiveness and efficiency improvement, as they need to survive and develop in fierce market competition. Compared to state-owned enterprises, non-state-owned enterprises may have more flexible decision-making mechanisms and faster response times, enabling them to identify and execute digital merger and acquisition strategies more quickly.State owned enterprises may be subject to more policy restrictions and regulation.More importantly, non-state-owned enterprises can achieve better corporate performance in digital mergers and acquisitions. This may be because non-state-owned enterprises can more effectively integrate culture and retain talent after mergers and acquisitions, ensuring the smooth integration and operation of digital technology, thereby improving the overall factor productivity of the enterprise.

Table 8 Heterogeneity Test Results of Property Rights Nature

	If soe=0	If soe=1
	TFP_OP	TFP_OP
DMA	0.172***	0.0903*
	(2.58)	(1.72)
age	0.000124	0.0558***
	(0.27)	(10.90)
NP	4.42e-11***	6.05e-11***
	(4.46)	(7.55)
lev	0.0000663	0.00267**
	(0.37)	(2.36)
_cons	6.756***	5.513***
	(93.13)	(39.28)
N	915	1154
df_m	3	3
r2	0.11	0.08

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 ROBUSTNESS TEST

The previous research indicates that digital mergers and acquisitions have a positive promoting effect on the total factor productivity of enterprises.To further enhance the robustness of the research conclusions, a series of robustness tests were conducted in this section, including replacing the dependent variable and adjusting the sample period, controlling for province fixed effects to address endogeneity issues.

7.1 Replacement of Dependent Variable

This section adopts the method of replacing the dependent variable for robustness testing, and selects the enterprise total factor productivity calculated by GMM method (TFP_GMM) to replace the enterprise total factor productivity calculated by OP method and OLS method in the original benchmark regression model for estimation. The results are shown in Table 9.

According to the results in Table 9, the coefficient between digital mergers and acquisitions (DMA) and total factor productivity (TFP_GMM) of enterprises is 0.182, and it is significant at the 1% significance level with a t-value of 4.25. This indicates that digital mergers and acquisitions (DMA) have a significant positive impact on total factor productivity (TFP_GMM).Even after replacing the dependent variable for robustness testing, this result remains robust, indicating that digital mergers and acquisitions can significantly improve the total factor productivity of enterprises.Meanwhile, due to the large sample size, the coefficient of determination of the model is 0.08, indicating that the model has a certain explanatory power.These results provide robust evidence for the study of the impact of digital mergers and acquisitions on total factor productivity.

Table 9 Results of Robustness Test

	(1) TFP_GMM
DMA	0.182^{***}
	(4.25)
age	0.000476^{***}
	(1.07)
NP	$5.50e\text{-}11^{***}$
	(8.42)
lev	0.000217^{***}
	(1.32)
_cons	5.740^{***}
	(121.93)
N	2069
df_m	3
r2	0.08

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7.2 Adjustment of Sample Period

Adjusting the sample period is a common method for robustness testing, which includes expanding the time window, shortening the time window, and rolling the window method.This section adopts the method of adjusting the sample period for robustness testing, by narrowing the time window. Shortening the time window can exclude the influence of other policies, economic cycles, etc., which helps to verify the stability and reliability of the research results.I have shortened the original sample period from 2015-2022 to 2017-2022 to test whether the conclusions on the impact of digital mergers and acquisitions on total factor productivity remain consistent across different time periods [16].
According to Table 10, it can be seen that the coefficient of DMA in the regression results after adjusting the sample period is positive and significant at the 1% significance level, indicating that digital mergers and acquisitions (DMA) have a significant positive impact on total factor productivity (TFP_OP).This means that digital mergers and acquisitions can significantly improve a company's total factor productivity while controlling for other variables.At the same time, the sample size is large, and the coefficient of determination of the model is 0.1062, indicating that the model has a certain explanatory power [17].

Table 10 Adjustment Results for Sample Period

	(1) TFP_OP
DMA	0.141^{***}
	(3.13)
age	0.000^{***}
	(0.11)
NP	0.000^{***}
	(6.98)
lev	0.000^{***}
	(-0.05)
_cons	6.985^{***}
	(6.09)
N	2069
df_m	4
r2	0.1062

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

8 RESEARCH CONCLUSIONS AND RECOMMENDATIONS

8.1 Research Conclusion

As the Chinese economy enters a stage of high-quality development, physical enterprises are facing a transformation and upgrading towards digitization and intelligence.This article selects micro panel data of Chinese A-share listed companies from 2015 to 2023 to conduct in-depth research on the relationship and mechanism between digital mergers and acquisitions and total factor productivity of enterprises.Research shows that digital mergers and acquisitions have a positive promoting effect on total factor productivity of enterprises;Mechanism research shows that digital mergers and acquisitions promote total factor productivity of enterprises by enhancing technological innovation, optimizing human capital structure, and innovating business models;Heterogeneity analysis found that non-state-owned enterprises have a more significant impact on total factor productivity in digital mergers and acquisitions.

8.2 Suggestions

8.2.1 Enterprises

1 In terms of technology, enterprises should continue to increase their investment in digital technology research and development to ensure that the technological advantages of both parties can be fully explored and integrated after digital mergers and acquisitions. Encourage R&D teams to carry out cross departmental and cross enterprise technical cooperation and exchanges. In addition, enterprises can continuously improve their technological level by building internal technology sharing platforms, actively attracting external digital technology experts and outstanding talents to join the enterprise, and providing talent reserves for technological innovation.Xiao B et al. found that green innovation has a significant impact on green total factor productivity, so further research can be conducted on technological innovation in green development [12]. In addition, Song C et al. found that improving the ESG performance of enterprises to achieve sustainable development is an important way for digital transformation to enhance total factor productivity [13].

2 In terms of human capital mechanism, enterprises should establish a scientific and reasonable human resource management system, formulate clear job responsibilities and performance evaluation standards, and promote the formation of a good team cooperation atmosphere through technical seminars and other means.In the process of digital mergers and acquisitions, enterprises should also pay attention to cultural integration and innovation, and form a distinctive corporate culture.

3 In terms of innovative business models, enterprises can take digital mergers and acquisitions as an opportunity to optimize and upgrade various aspects of production, sales, management, etc. using digital technology. They can also obtain new business resources and market channels through digital mergers and acquisitions, expand their business scope and profit margins.In addition, enterprises should also strengthen their awareness of property rights protection.Yang Y et al. demonstrated through using data from Chinese listed companies as a sample study that digital transformation can promote TFP of enterprises by enhancing innovation capabilities and cost control [14].

8.2.2 Government

The government should introduce a series of policies and measures to support digital mergers and acquisitions, encourage enterprises to actively engage in digital mergers and acquisitions activities, increase the construction of digital economic infrastructure, provide a favorable hardware environment for digital mergers and acquisitions and the development of new quality productivity, and establish a sound regulatory mechanism for digital mergers and acquisitions, strengthening guidance for enterprise digital mergers and acquisitions.

8.2.3 Society

All sectors of society should actively establish innovation service platforms, create a social culture that encourages innovation and tolerates failure, and enhance the innovation awareness and ability of the whole society.We should focus on the relationship between digital mergers and acquisitions and labor productivity, and pay particular attention to the impact of knowledge distance between merging parties [15]. Secondly, educational institutions should strengthen the cultivation of digital talents, cultivate compound talents with digital technology and innovation capabilities, strengthen cooperation with enterprises, and promote the optimization and sharing of talent resources.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

FUNDING

This work was financially supported by the Key Project of the National Social Science Foundation of China《Research on the Mechanism, Path, and Policy of Digital Technology-Driven Virtual Transformation of Industrial Clusters》(23AJY005).

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3056

RESHAPING THE COMPETENCY STRUCTURE AND TRANSFORMING THE CULTIVATION MODEL OF SCIENTIFIC AND TECHNOLOGICAL TALENT IN THE ERA OF ARTIFICIAL INTELLIGENCE

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Abstract: Artificial intelligence (AI) is profoundly transforming industries and society, placing new demands on the competency structure of technology professionals. This paper explores the urgent need and pathways for reshaping the competencies of technology professionals and transforming their cultivation models in the AI era. The research indicates that the traditional mono-disciplinary competency structure is no longer suited to the complex innovation environment driven by AI, necessitating the construction of a composite competency system encompassing data thinking, algorithm application, interdisciplinary integration, innovation capability, and lifelong learning. Existing cultivation models exhibit limitations in interdisciplinary focus, innovation cultivation, knowledge update speed, and ethical awareness. To address this, this paper constructs a model comprising six core competency elements: professional technical skills, data processing, innovation, interdisciplinary integration, learning adaptation, and team collaboration. It proposes pathways for competency reshaping from four levels: government, higher education institutions, enterprises, and individuals. Key to transforming the cultivation model are: updating educational philosophies (emphasizing lifelong learning and innovation), innovating teaching methods (e.g., PBL, flipped classrooms), optimizing curriculum systems (integrating cutting-edge knowledge and strengthening interdisciplinary elements), and deepening industry-education integration. Analysis of domestic and international case studies validates the effectiveness of the proposed strategies. Successful transformation is strategically significant for enhancing individual competitiveness and driving national scientific and technological innovation and high-quality development.
Keywords: Artificial intelligence era; Technology professionals; Competency restructuring; Cultivation model transformation; Interdisciplinary integration; Innovation capability

1 INTRODUCTION

With the rapid advancement of technology, the advent of the artificial intelligence era has profoundly reshaped global industrial landscapes and societal lifestyles. As a pivotal force driving future development, AI technology is redefining the core elements of productivity, catalyzing the transformation and upgrading of traditional industries and the emergence of new sectors. Against this backdrop, technology professionals—key agents of scientific progress and innovation—face unprecedented demands to restructure their competencies. Traditional cultivation models for such talent have become inadequate for the new era, necessitating urgent transformation. The imperative to reshape the competency structure of technology professionals and transform their cultivation models lies in the new challenges posed by AI technology regarding knowledge frameworks, skill requirements, and innovation capabilities. Past cultivation models, predominantly focused on specialized knowledge, are insufficient to meet the demand for compound, innovative talent in the AI era. Consequently, reconstructing the competency structure of technology professionals and designing cultivation models aligned with contemporary needs have become focal points for both educational and industrial communities. This paper aims to explore pathways for reshaping the competency structure of technology professionals and strategies for transforming cultivation models in the AI era. By examining existing education and training systems, analyzing their deficiencies, and integrating characteristics of the AI era, it proposes corresponding reform recommendations. This research holds significant theoretical and practical value for enhancing the cultivation and development of China's technology professionals, advancing scientific and technological innovation, and adapting to new dynamics of international competition. Addressing this issue will not only improve the quality of talent cultivation but also provide enduring talent provision and intellectual support for China's long-term scientific and technological advancement.

2 CURRENT STATE OF AI DEVELOPMENT AND EVOLUTION OF COMPETENCY STRUCTURE & CULTIVATION MODELS FOR TECHNOLOGY PROFESSIONALS

2.1 Current State of Artificial Intelligence Development

Since the introduction of the Transformer architecture, it has been widely applied and continuously developed in fields such as natural language processing and computer vision. In recent years, researchers have made numerous improvements and extensions based on the Transformer. For instance, efficient variants suitable for long sequence processing have been proposed. Models like Longformer, by introducing a local attention mechanism, can significantly reduce computational load and enhance processing efficiency when handling ultra-long texts, enabling the processing of texts such as novels and academic papers, thereby expanding the application scenarios of natural language processing. To leverage the strengths of different model architectures, researchers have begun exploring the fusion of multiple architectures. Examples include combining Convolutional Neural Networks (CNN) with Transformers, exploiting CNN's advantage in feature extraction and the Transformer's capability in capturing long-range dependencies. Such hybrid architectures demonstrate superior performance in image and video processing tasks. Large language models represented by GPT-4 are continually setting new parameter records. With massive parameters, these large models can learn richer linguistic knowledge and patterns, exhibiting remarkable capabilities in language understanding, generation, and reasoning. For example, GPT-4 can perform complex text creation, dialogue interaction, and even excel in tests within specialized domains. Beyond the text domain, multimodal large models have become a research hotspot. Multimodal large models can simultaneously process various types of data such as images, text, and audio, enabling more comprehensive information understanding and processing. For instance, some multimodal models can generate descriptive text from images or create relevant images from text. This cross-modal interaction capability endows intelligent systems with more powerful functions and broader application prospects. Deep reinforcement learning has made significant progress in fields like robotics control, gaming, and autonomous driving. By integrating deep learning with reinforcement learning, agents can autonomously learn optimal strategies in complex environments[1]. In robotics, for example, deep reinforcement learning enables robots to navigate autonomously in unknown environments and perform grasping and manipulation tasks. In gaming, reinforcement learning algorithms allow agents to reach the level of top human players in complex game environments. Imitation learning, a branch of reinforcement learning, achieves intelligent decision-making by learning from human expert behavior. Recently, imitation learning has achieved notable results in complex tasks, such as imitating human driver behavior in autonomous driving scenarios, enabling efficient driving while ensuring safety.

Artificial intelligence technology plays a crucial role in medical imaging diagnosis. Deep learning algorithms can analyze medical images such as X-rays, CT scans, and MRIs, assisting doctors in detecting diseases like lung cancer and breast cancer. For example, some AI-based medical imaging diagnosis systems can accurately identify pathological features in images, improving early disease diagnosis rates. AI can predict drug activity and side effects by analyzing vast amounts of biological data and chemical structures, accelerating the drug development process. Through computer simulations and machine learning algorithms, it can rapidly screen potential drug molecules, reducing development cycles and costs. Banks and financial institutions utilize AI algorithms to assess clients' credit risk. By analyzing multi-dimensional data including credit history, financial status, and consumer behavior, they can more accurately predict clients' default probability, lowering credit risk. The application of AI in the investment field is also increasingly widespread. Quantitative investment strategies use machine learning algorithms to analyze market data, uncover investment opportunities, and optimize portfolios. Some robo-advisory platforms can provide personalized investment advice based on investors' risk preferences and financial goals. AI technology can provide personalized learning plans based on students' learning progress, learning style, and knowledge mastery. Intelligent tutoring systems can monitor students' learning processes in real-time, identify their weaknesses, and provide targeted tutoring and exercises. Virtual teaching assistants can answer student questions, provide learning resources, and assist teachers with instructional management. For example, some AI-based chatbots can address common student queries, reducing teachers' workload. AI is the core of autonomous driving technology. Through sensors, cameras, and algorithms, autonomous vehicles can perceive their surroundings, make real-time decisions, and achieve automatic navigation and obstacle avoidance. Currently, many automakers and tech companies are actively developing autonomous driving technology, with testing and pilot applications underway in some cities. Using AI technology to monitor and analyze traffic flow in real-time can optimize traffic signal control and alleviate urban congestion. For instance, some cities employ intelligent traffic systems that dynamically adjust traffic light timing based on flow, improving road efficiency. AI applications in entertainment content creation are becoming increasingly widespread. In music composition, AI can generate melodies and lyrics; in film and television production, it can be used for special effects and scene generation. For example, some AI-generated music works have gained attention online. AI technology can add smarter opponents and richer experiences to games. Non-player characters (NPCs) in games can utilize AI algorithms to exhibit more complex behaviors and decisions, enhancing the game's fun and challenge[2].

2.2 Evolution of the Competency Structure of Technology Professionals

2.2.1 Evolution process of technology professionals' competency structure

In the pre-Industrial Revolution era, technological activities were primarily concentrated in the fields of handicraft and simple mechanical invention. Technology professionals during this period were mostly artisans and craftsmen. Their competency structure emphasized specific manual skills and the use of simple tools. For instance, in the textile industry, artisans possessed proficient weaving techniques and could use simple textile tools to produce various fabrics; in metalworking, artisans mastered skills like forging and casting to create practical metalware. Their knowledge mainly stemmed from long-term practical experience passed down through generations, with relatively less systematic mastery of theoretical knowledge. The competency structure of technology professionals at this time was relatively singular, focused primarily on specific operational skills, with low demand for cross-domain comprehensive abilities. The rise of the Industrial Revolution brought changes to the competency structure of technology professionals[3]. With the emergence of machine production, they needed to master knowledge of mechanical principles, engineering drawing, etc., to design and manufacture machinery. For example, during the steam power era, technology professionals needed to understand thermodynamic principles and master the design and manufacturing techniques of steam engines. They required not only practical operational abilities but also a certain level of theoretical knowledge and innovative capability to improve and innovate upon traditional production methods. During this period, technology professionals began to develop along specialized paths, and the differences in competency structures across various fields became increasingly apparent[4].

2.2.2 Changes in the competency structure of technology professionals in the early stage of the Information Technology Revolution

In the mid-20th century, the Information Technology Revolution quietly emerged, and computer technology began to develop. At this stage, technology professionals needed to master skills like computer programming and algorithm design to develop software and write programs. Early computers were mainly used for scientific computing and data processing, requiring technology professionals to possess solid mathematical foundations and logical thinking skills to write efficient algorithms and programs. For instance, in the early mainframe era, technology professionals needed to be familiar with assembly language, capable of interacting directly with computer hardware, and have a deep understanding of the underlying principles of computer systems. With the initial development of the internet, the competency structure of technology professionals further expanded. In addition to programming skills, knowledge of network technology, database management, etc., became necessary[5]. They needed to be able to build and maintain network systems and manage and process large amounts of data. For example, when e-commerce was just emerging, technology professionals needed to develop and maintain e-commerce platforms. This required them not only to master front-end web design technologies but also to understand back-end database management and server configuration to ensure platform stability and data security.

2.2.3 Transformation of the competency structure of technology professionals during the rapid development period of information technology

Entering the 21st century, with the rapid development of technologies like big data and artificial intelligence, the competency structure of technology professionals underwent significant changes. They now need to possess interdisciplinary knowledge and capabilities, integrating knowledge from computer science, mathematics, statistics, biology, and other disciplines. For example, in the field of bioinformatics, technology professionals need to combine computer technology with biological knowledge, using algorithms and models to analyze and interpret biological data to advance research in genetics, drug development, etc. Faced with rapidly changing technological environments and complex real-world problems, technology professionals need strong innovative capabilities and problem-solving skills. They must be able to quickly adapt to new technological developments and propose novel solutions. For instance, when confronting data privacy and ethical issues in AI algorithms, they require innovative thinking to formulate corresponding technical and management strategies to address these problems. The big data era has generated massive volumes of data, necessitating that technology professionals possess a series of data processing capabilities including data collection, storage, cleaning, analysis, and visualization. They need to be able to use various data analysis tools and techniques to extract valuable information from large datasets to support decision-making[6]. For example, in the financial sector, technology professionals analyze market data to predict trends and provide basis for investment decisions. The advancement of information technology has made technology projects increasingly complex, often requiring collaboration among individuals with diverse professional backgrounds. Technology professionals need strong teamwork and communication skills to interact and collaborate effectively with personnel from different fields. For instance, a large AI project might involve roles such as algorithm engineers, data scientists, and product managers; technology professionals need to work closely with team members to ensure the project proceeds smoothly. The rapid development of information technology has accelerated the pace of knowledge and technology updates, requiring technology professionals to possess awareness and capability for lifelong learning. They must continuously learn new knowledge and skills to adapt to technological changes. For example, with the constant updates to programming languages and development frameworks, technology professionals need to promptly learn and master new technologies to maintain their competitiveness[7].

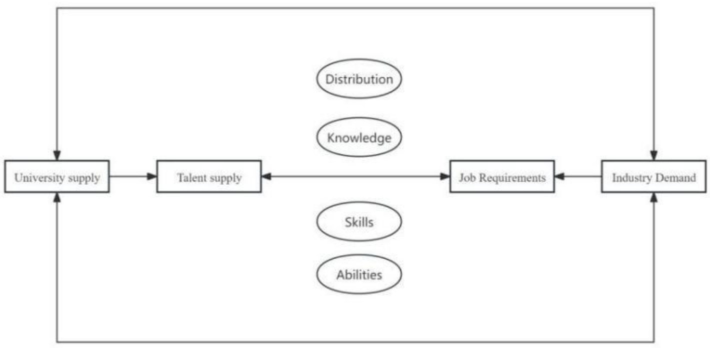

Figure 1 Theoretical Analysis Framework

The industrial demands of the new era are reflected in the job requirements of enterprises and institutions. As a key supplier of high-value-added labor, higher education institutions must cultivate a workforce aligned with these job demands. Such a labor market characterized by supply-demand matching serves as an essential foundation for industrial development. Based on this, the theoretical analytical framework of this study is formed (see Figure 1). This research takes AI talent as the study object, with the supply-demand balance between industrial needs and higher education supply as its logical starting point. It focuses on the matching degree between job requirements and talent supply, using factors such as labor distribution, knowledge, skills, and competencies as analytical elements for evaluating supply-demand matching in the AI labor market[8].

2.2.4 Future development trends of technology professionals' competency structure

With the continuous emergence and integration of emerging technologies such as quantum computing, biotechnology, and new energy, future technology professionals will require more comprehensive competencies. They must not only master foundational knowledge across multiple technical domains but also integrate and innovate with technologies from different fields. For example, in the interdisciplinary area of quantum information technology and biotechnology, technology professionals need to simultaneously understand quantum mechanics, computer science, and biology to develop innovative technologies and applications. The globalization of technology necessitates that technology professionals possess a global perspective, understanding technological developments and cultural contexts across different countries and regions. They must engage in effective communication and collaboration with international peers and participate in global technology projects and competitions. For instance, when addressing global environmental issues and public health crises, technology professionals need to collaborate with research teams worldwide to tackle complex challenges collectively.

2.3 Review of Existing Cultivation Models

2.3.1 Strengths of existing cultivation models for technology professionals

Current cultivation models emphasize building systematic and comprehensive professional knowledge systems during undergraduate and graduate studies. Taking computer science as an example, students systematically study foundational courses such as data structures, computer organization principles, and operating systems during their undergraduate years, while graduate studies delve deeper into cutting-edge fields like artificial intelligence and machine learning. This thorough knowledge transmission enables students to gain profound understanding and mastery of their disciplines, laying a solid theoretical foundation for future research and technical work. To cultivate practical operational and problem-solving abilities, many universities and research institutions have enhanced practical teaching components. For example, electronic information engineering programs include hands-on courses like electronic circuit experiments and microcontroller design, allowing students to consolidate theoretical knowledge and improve practical skills[9]. Additionally, internships and capstone projects provide opportunities to engage with real-world engineering problems, integrating theory with practice and better preparing students for future career demands. Amid globalization, existing cultivation models increasingly prioritize international exchange and collaboration. Through joint programs and academic exchanges with renowned foreign universities and enterprises, higher education institutions offer students broader global exposure. Students access cutting-edge international research and academic ideas and collaborate with top global research teams, fostering innovative thinking and international competitiveness.

2.3.2 Weaknesses of existing cultivation models

In today’s rapidly evolving technological landscape, many complex scientific and engineering problems require interdisciplinary knowledge integration. However, existing cultivation models often overemphasize single-discipline knowledge transmission, with limited cross-disciplinary courses, leaving students deficient in interdisciplinary thinking and capabilities. For instance, in the intersection of AI and medicine, there is a severe shortage of professionals proficient in both AI technology and medical knowledge. Under traditional cultivation models, medical students lack AI-related knowledge, while computer science students have minimal medical understanding, failing to meet industry demands. Although practical teaching has been strengthened, innovation cultivation remains inadequate. Current teaching methods predominantly rely on instructor-led lectures, with students passively receiving knowledge and lacking opportunities for active exploration. In experiments and practical courses, students often follow predefined procedures with little room for autonomous innovation. Furthermore, evaluation systems overemphasize exam scores and publication counts, neglecting assessments of innovative thinking and practical skills, which stifles students’ creative enthusiasm.

2.3.3 Limitations of existing models in the AI era

The rapid advancement of AI technology sees constant emergence of new algorithms, models, and applications. Knowledge taught in existing cultivation models often lags, with outdated textbooks and curricula failing to reflect the latest technological developments. For example, many current AI courses in universities still focus on traditional machine learning algorithms, with minimal coverage of recent advancements like Transformer architecture and Generative Adversarial Networks (GANs). This disconnect leaves students ill-prepared for the fast-evolving technical demands of the AI era. The widespread application of AI has triggered ethical and social issues—data privacy, algorithmic bias, employment restructuring—yet existing cultivation models prioritize technical knowledge over AI ethics and societal impact education. Students lack deep engagement with these issues, risking oversight of AI’s potential risks and negative consequences in future work. In the AI era, human-AI collaboration will become critical. However, current models focus narrowly on professional skills, neglecting training in collaborative capabilities with AI systems. Students lack experience in interacting and co-working with AI, unaware of how to leverage its strengths while compensating for its limitations. For instance, in software development, students may not know how to use AI-assisted programming tools to enhance efficiency or collaborate effectively with AI customer service systems. This hinders future workplace efficacy and productivity[10].

3 RESHAPING THE COMPETENCY STRUCTURE OF TECHNOLOGY PROFESSIONALS IN THE AI ERA

3.1 Analysis of New Competency Requirements

The AI era has triggered unprecedented transformations in technology, demanding a restructured competency framework for professionals. Traditional specialized skills are insufficient for complex, dynamic technological and societal needs. Technology professionals now require new competencies to thrive in an AI-driven innovation landscape. Key emerging competencies are analyzed below.

3.1.1 Data thinking

In the AI era, data is the core resource driving decisions and innovation. Technology professionals need sharp data insight to extract valuable patterns from massive, complex datasets. This requires mastery of data analysis tools (e.g., statistics, machine learning algorithms) and critical thinking to interpret and evaluate data. For example, analyzing clinical data can reveal disease risk factors and treatment efficacy variations, enabling precision medicine. Professionals with data thinking use data—not just intuition—as the basis for decisions. They build data-driven decision models to evaluate options scientifically. In business management, analyzing market data and customer feedback helps optimize product strategies and marketing plans, enhancing competitiveness. With widespread data use, ethical and security concerns intensify. Professionals must uphold data ethics, comply with laws and moral standards, and ensure legal data usage. They also need data security awareness to protect privacy and prevent breaches. For instance, designing AI systems requires anonymization and access controls to safeguard user rights.

3.1.2 Algorithmic understanding and application

AI's core lies in algorithms. Professionals must deeply understand algorithmic principles and applicable scenarios, including machine learning (e.g., neural networks, decision trees) and deep learning algorithms (e.g., CNN, RNN). Mastering principles enables better algorithm selection and optimization. For example, understanding CNN principles improves image classification model design in computer vision. Beyond comprehension, professionals need algorithm design and optimization skills. They must create suitable algorithms for specific problems and refine performance through experimentation. In natural language processing, optimizing machine translation may involve designing new architectures with attention mechanisms. Applying algorithms to real-world scenarios to solve problems and innovate is crucial. For instance, using algorithms for real-time traffic monitoring and prediction enables smart signal control, boosting efficiency. Exploring new application scenarios drives industry transformation.

3.1.3 Interdisciplinary collaboration

AI-era problems are complex and multifaceted, requiring interdisciplinary knowledge integration. Professionals need cross-disciplinary knowledge systems to fuse complementary expertise. For example, smart healthcare demands integration of computer science, medicine, and biology to develop diagnostic systems and personalized treatments. Continuous learning across disciplines broadens perspectives. Interdisciplinary collaboration hinges on teamwork and communication. Professionals must collaborate effectively with diverse experts to achieve project goals. Clear articulation of ideas, understanding others' viewpoints, and leveraging team strengths are essential. Strong communication with team members, clients, and partners ensures project success. Globalization necessitates cross-cultural and cross-domain exchange capabilities. Professionals must engage with international peers, understand global tech trends, and respect cultural differences. Learning from other fields' best practices accelerates innovation.

3.1.4 Innovation and entrepreneurship

The AI era is innovation-driven. Professionals must embrace innovative thinking, break traditional paradigms, and propose novel solutions. Cultivating curiosity and staying abreast of technological frontiers enables exploration of new applications. For example, identifying real-world problems and developing AI-driven products/services meets emerging needs. Innovation requires translating ideas into tangible outcomes. Professionals must validate ideas through experimentation and refine results continuously. In entrepreneurship, launching innovative products to market achieves commercial value. Resilience in overcoming challenges and adapting strategies is vital. Aspiring entrepreneurs need entrepreneurial spirit and competencies. Courage to take risks in uncertain environments, leadership to build and manage teams, and skills in market analysis, business planning, and financial management are essential for venture success.

3.1.5 Lifelong learning

In the rapidly evolving AI era, knowledge and technology constantly renew. Professionals must embrace lifelong learning, recognizing it as an ongoing process to enhance capabilities. Maintaining enthusiasm for new knowledge and proactively acquiring skills ensures adaptability. Effective learning strategies boost efficiency. Diverse approaches—online courses, training programs, professional literature—should be utilized. Structured learning plans, systematic study, and reflective practice optimize outcomes. In the information age, leveraging and integrating resources is key. Professionals must filter and utilize resources from the internet, libraries, and academic databases. Engaging with peers and experts to share resources and experiences fosters collective growth.

In summary, the AI era demands a multifaceted competency structure for technology professionals. Mastery of data thinking, algorithmic expertise, interdisciplinary collaboration, innovation, entrepreneurship, and lifelong learning is essential to adapt to technological and societal shifts. Continuous competency enhancement ensures competitiveness and significant contributions to technological and societal progress[11].
Course content in university AI programs fails to meet industry demands for interdisciplinary and general knowledge. Industry surveys reveal that enterprises require three knowledge types: AI expertise, domain-specific knowledge (e.g., medicine, finance), and general knowledge. However, university curricula focus predominantly on AI expertise (applied, core, tool-based, and foundational courses), with only 22.20% covering interdisciplinary and general knowledge. This gap impedes alignment with industry needs. Constructing interdisciplinary curricula is challenging. Survey results indicate that AI professionals require knowledge spanning diverse fields—management, economics, philosophy, law, education, history, etc. (see Figure 2)—making curriculum design complex.

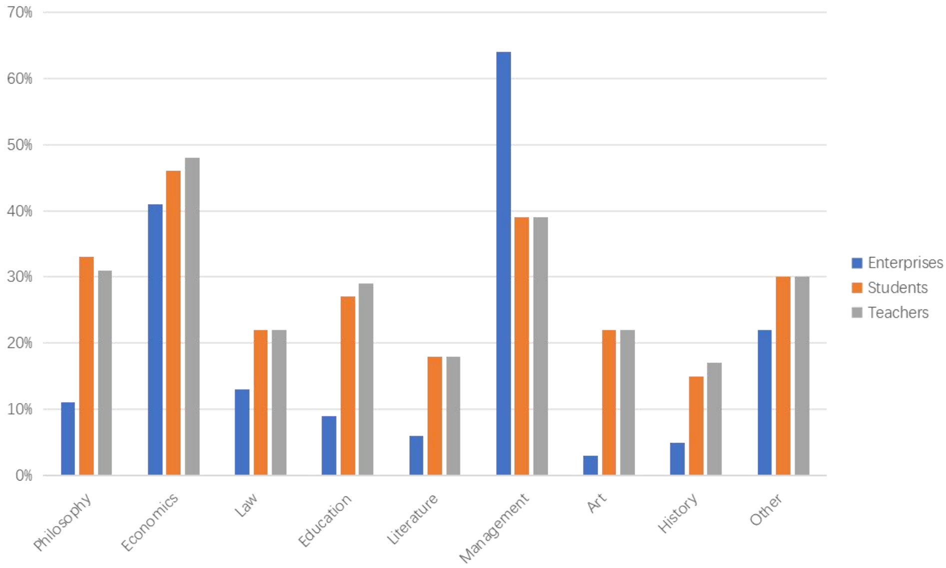

Figure 2 Relevant Subject Knowledge Required by AI Professionals from the Perspectives of Enterprises, Students, and Teachers

3.2 Competency Structure Model Construction

In the artificial intelligence era, technology professionals confront novel challenges and opportunities. Constructing a competency structure model adapted to this epoch is pivotal for cultivating and developing such talent. This section establishes a multidimensional competency structure model for technology professionals and delineates the interrelationships among its constituent elements.

3.2.1 Identification of model elements

Through comprehensive analysis of AI-driven technological trends, industry demands, and requisite competencies, six core elements form the model. Professional technical competency serves as the foundation for innovation and practice within specific domains. In the AI era, professionals must master cutting-edge theoretical knowledge and key technologies in their disciplines—such as algorithm design, programming languages (e.g., Python, Java), and machine/deep learning model construction in computer science; or chip design and circuit principles in electronic engineering. Solid technical expertise enables professionals to play pivotal roles in research and engineering projects. Data, as the core resource of the AI era, necessitates robust data processing and analytical capabilities. This encompasses data collection, cleaning, storage, visualization, and utilization of tools (e.g., SQL, R, Tableau) for mining insights. Extracting actionable intelligence from massive datasets constitutes a critical competitive advantage. The rapid evolution of AI propels continuous technological innovation, demanding innovative thinking and creativity. Innovative thinking—spanning divergent, reverse, and critical thought—breaks conventional constraints to propose novel solutions. Creativity manifests in transforming ideas into products, technologies, or services that advance industries. AI-era challenges often exhibit complexity and multidimensionality, requiring interdisciplinary integration capabilities. For instance, medical AI fuses computer science, medicine, and biology; smart mobility integrates transportation engineering, control science, and AI. This competency dismantles disciplinary barriers, merging resources and methodologies to solve real-world problems[12]. Rapid technological turnover mandates strong learning and adaptability. Professionals must swiftly acquire new knowledge/skills and adapt to evolving technical demands. Continuous learning—through training, academic exchanges, and self-directed study—sustains competitiveness. Collaborative projects increasingly demand teamwork across specialties. Effective collaboration and communication skills—including team ethos, leadership, and conflict resolution—enable professionals to synergize diverse strengths, enhancing project efficacy.

3.2.2 Interrelationships among competency elements

Elements exhibit interdependence: professional technical competency underpins data processing/analysis, as domain expertise ensures accurate data interpretation. Conversely, data analysis informs technical innovation by revealing patterns and improvement opportunities. Mutual reinforcement also exists: innovative thinking fuels learning motivation, enhancing adaptability; improved adaptability enriches knowledge reservoirs, further driving innovation. Similarly, interdisciplinary integration fosters collaboration skills in diverse teams, while strong collaboration facilitates cross-disciplinary knowledge synthesis[13]. The competency structure constitutes a dynamic system: elements evolve with technological progress and individual growth. As AI proliferates, professionals must continuously recalibrate their competencies—e.g., intensifying data analysis and innovation capabilities to meet emergent demands. This model elucidates competency interrelationships, offering theoretical and practical guidance for cultivating, developing, and evaluating technology professionals. Enhancing these competencies elevates holistic quality and competitiveness, propelling technological advancement in the AI era.

3.3 Pathways for Competency Restructuring

Reshaping the competency structure of technology professionals in the AI era demands a systemic, multi-stakeholder approach. Governments, universities, enterprises, and individuals must collaborate through policy guidance, educational reform, practical training, and self-improvement.

3.3.1 Government level: policy guidance and resource support

Governments should formulate policies aligned with AI-driven technological trends. Policies should encourage interdisciplinary learning and research—for instance, establishing dedicated funds for cross-domain projects to dismantle disciplinary silos. Concurrently, talent recruitment and retention policies must attract overseas experts while enhancing domestic professionals' development environments to curb brain drain. Increased fiscal investment in education—particularly AI-related disciplines—is essential. Supporting universities and vocational institutions in launching cutting-edge programs (e.g., AI, big data, machine learning) and upgrading infrastructure is critical. Dedicated training funds should incentivize enterprises and institutions to deliver continuing education for upskilling professionals. Governments must actively foster industry-academia-research integration by organizing international/domestic conferences, seminars, and innovation contests to facilitate knowledge exchange. Establishing talent-sharing mechanisms will promote mobility and collaboration across regions, enterprises, and research entities.

3.3.2 University level: educational reform and innovative cultivation

Universities must optimize curricula to build interdisciplinary structures aligned with AI-era demands. Beyond traditional courses, integrating AI, information technology, and data analytics across disciplines cultivates interdisciplinary thinking—e.g., embedding AI algorithms in STEM fields and data mining in humanities programs. Strengthening practical pedagogy enhances hands-on and innovative capacities. Partnerships with enterprises and research institutes to co-establish internships and innovation platforms provide real-world project exposure. Encouraging participation in academic competitions and entrepreneurial activities hones teamwork and problem-solving skills[14]. Faculty competence—particularly in AI application—requires enhancement through training, interdisciplinary research incentives, and recruiting industry-experienced adjunct professors. Leveraging prevailing AI technologies (e.g., intelligent platforms, AI teaching assistants, machine learning) to reform pedagogical methods can effectively address these gaps. Fundamentally, the future "AI + education" model should evolve toward personalization, intelligence, accessibility, and timeliness (Figure 3).

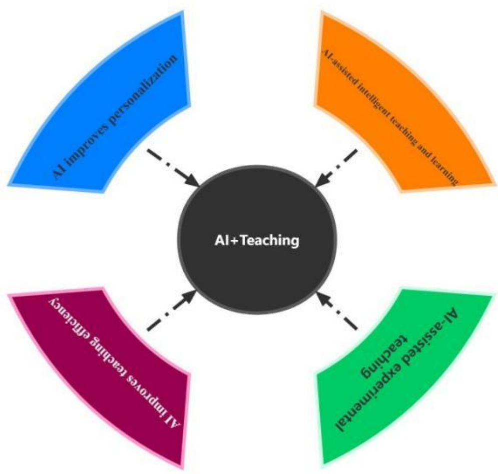

Figure 3 The Integration Direction of AI Technology and College Chemistry Teaching

3.3.3 Enterprise level: practical training and incentive mechanisms

Enterprises should actively provide technology professionals with practical training opportunities by involving them in actual projects and R&D initiatives. Establishing a project mentorship system where experienced technical experts guide new hires facilitates rapid growth. Concurrently, professionals should be encouraged to participate in technological and managerial innovation, contributing insights to corporate development. Robust incentive mechanisms must be instituted to stimulate innovation motivation. Innovation reward funds should offer material and recognition-based incentives for outstanding achievements in technological innovation, product development, and management improvement. Furthermore, clear career progression paths should enable professionals to realize their value within the organization. Enterprises must enhance internal training by conducting tailored programs aligned with professional needs and roles—e.g., AI workshops and data analytics seminars—to elevate technical and holistic competencies. Support for self-directed learning through resource provision is equally critical.

3.3.4 Individual level: self-improvement and lifelong learning

Technology professionals must embrace lifelong learning, recognizing that accelerated knowledge and technological obsolescence in the AI era necessitates continuous self-upgrading. Maintaining learning enthusiasm and proactively tracking industry trends is essential. Personalized learning plans should address career goals and competency gaps, prioritizing frontier technologies (e.g., AI, big data, cloud computing) and interdisciplinary knowledge acquisition through courses, online platforms, and literature. Cultivating innovative thinking requires breaking conventional paradigms and experimenting with novel approaches[15]. Engaging in cross-domain collaboration sparks creative inspiration, while critical thinking enables deep analysis of knowledge and techniques. Collectively, competency restructuring demands concerted efforts from governments, universities, enterprises, and individuals. Implementing these pathways will optimize talent capabilities, providing robust human capital for AI-driven technological advancement.

4 TRANSFORMATION STRATEGIES FOR CULTIVATION MODELS

4.1 Updating Educational Philosophies

To align education with contemporary demands and cultivate talent suited to societal needs, updating educational philosophies is imperative. AI-era education must prioritize lifelong learning and innovation as core pillars of a restructured system. Traditional models emphasizing knowledge transmission and memorization are obsolete amid rapid knowledge turnover. New philosophies should focus on cultivating comprehensive competencies for navigating complex challenges. Education must foster critical thinking and problem-solving abilities. While AI excels at data processing, human judgment remains irreplaceable for creative problem-solving. Guiding students to critically evaluate information, pose questions, and devise solutions—e.g., through case-based group discussions—enhances independent thinking and practical problem-solving. Cross-disciplinary integration is equally vital. AI’s multidisciplinary nature (spanning computer science, mathematics, statistics, psychology) demands interdisciplinary vision. Universities should offer cross-disciplinary courses and projects to facilitate knowledge synthesis.

Lifelong learning is non-negotiable. Frequent career transitions necessitate continuous skill renewal. Education must instill lifelong learning awareness beyond formal schooling. Educators should cultivate growth mindsets by illustrating technological and occupational shifts. Providing diverse resources—open libraries, labs, lectures, and training—encourages self-directed exploration. Teaching learning strategies (e.g., time management, digital resource utilization, self-assessment) sustains post-graduation upskilling. Innovation constitutes the core competitiveness in the AI era. Educational environments must stimulate creativity through innovation courses, competitions, and design challenges. Recognizing individual strengths enables personalized development—e.g., nurturing artistic talent or scientific curiosity. Ultimately, an educational philosophy centered on lifelong learning and innovation empowers individuals to thrive and drive societal progress.

4.2 Innovative Teaching Methods

4.2.1 Application of Project-Based Learning (PBL) in cultivating technology professionals

Project-Based Learning (PBL), a student-centered approach, engages learners in authentic projects to acquire knowledge and skills. In technical education, PBL simulates real-world scenarios, enhancing comprehensive abilities through problem-solving. Instructors should select challenging, interdisciplinary project themes—e.g., developing mobile applications in computer science programs—encompassing requirements analysis, design, coding, and testing. Students form diverse teams to foster complementary collaboration. Instructors act as facilitators, providing guidance while encouraging autonomy. Post-project evaluation includes teacher/peer reviews and presentations to hone communication skills. PBL bridges theory and practice, elevating technical, collaborative, and innovative capacities. Implementation requires experienced instructors, institutional resources, and strategies to ensure universal engagement.

4.2.2 Application of flipped classrooms in cultivating technology professionals

The flipped classroom inverts traditional teaching: students self-learn theory before class via videos/materials, while class time focuses on discussion, practice, and Q&A. Instructors prepare concise video lectures highlighting key concepts and provide online support. In-class activities include peer discussions, project implementation, and individualized guidance. Post-class assignments (e.g., reports, summaries) consolidate learning, supplemented by recommended resources for deeper exploration. This model enhances flexibility and engagement, fostering collaboration and personalized instruction. Success depends on students’ self-discipline and instructors’ technological and pedagogical proficiency[16].

4.2.3 Integration and practice of innovative teaching methods

Blending methods like PBL and flipped classrooms maximizes educational outcomes. For instance, pre-class flipped learning delivers theoretical foundations for in-class PBL implementation, optimizing efficiency. A case in electronic information engineering demonstrates this synergy: students studied project theory online before class, then executed team projects in supervised sessions with peer discussions. This hybrid approach boosted engagement and output quality. Successful integration requires institutional investment in digital platforms and practical facilities, continuous teacher training in pedagogy and technology, and evaluative mechanisms for iterative refinement.In addition,AI enterprises demand not only specialized knowledge and technical skills but also exhibit strong requirements for versatile competencies. Consequently, higher education institutions should prioritize integrating general education courses into AI curricula to cultivate students' transferable skills.

5 CASE ANALYSIS

5.1 Successful Cases Domestically and Internationally

Germany's traditional manufacturing industry holds significant global advantages. However, with the advancement of the technological revolution, particularly the introduction of the Industry 4.0 concept, the demand for scientific and technological talents has shifted from purely skill-based to compound talents equipped with digital and intelligent technology application capabilities. The traditional vocational education model exhibits deficiencies in cultivating students' ability to address emerging technological challenges, prompting Germany to transform its dual-system vocational education model. Building upon the original integration of practice and theory, emerging technology courses such as digital technology, industrial Internet of Things, and big data analytics have been added. For example, in the mechanical manufacturing major, students are required not only to learn traditional machining techniques but also to master programming and operation of CNC machine tools, application and maintenance of industrial robots, and other knowledge. Enterprises deeply participate in school curriculum development and teaching processes. Based on their production needs and industry development trends, enterprises collaborate with schools to formulate syllabi and practical projects. Simultaneously, enterprises provide schools with advanced production equipment and internship bases, while schools supply enterprises with high-quality talents meeting their development needs. Training for vocational education teachers has been strengthened, requiring teachers to possess not only solid theoretical knowledge but also extensive practical enterprise experience. Teachers regularly engage in practical training at enterprises to understand the latest industry technologies and production processes, enabling them to integrate real-world cases into teaching. Through the transformation of the dual-system vocational education model, Germany has cultivated a large number of scientific and technological talents adapted to Industry 4.0 development, maintaining its leading position in high-end manufacturing. Graduates are in high demand in the job market, and enterprises have seen significant improvements in production efficiency and innovation capabilities. Emphasizing industry-education integration is key to cultivating scientific and technological talents. Close collaboration between enterprises and schools ensures that talent cultivation aligns closely with market demands. Meanwhile, the curriculum system should keep pace with technological development trends, updating teaching content promptly to cultivate students' innovation and adaptability. As a frontier city of technological innovation in China, Shenzhen has experienced rapid industrial development, with demand for scientific and technological talents characterized by diversification and high-end specialization. In its early stages, the Shenzhen Research Institute of Tsinghua University primarily focused on transforming scientific research achievements. However, recognizing shifting market demands, it has consciously transformed into a comprehensive innovation talent cultivation platform integrating scientific research, education, and industrial incubation. An innovation and entrepreneurship curriculum system has been established, covering technological innovation, business model innovation, management innovation, and other aspects. Through teaching methods such as case analysis, project practice, and entrepreneurship simulation, students' innovative thinking and entrepreneurial capabilities are cultivated. The institute integrates Tsinghua University's scientific research resources with Shenzhen's industrial resources to establish multiple industry-university-research collaboration bases. Researchers, teachers, and students can conduct scientific research projects within these bases, engaging in deep cooperation with enterprises to accelerate the transformation and application of research achievements. Active international exchanges and collaborations have been carried out, establishing partnerships with renowned foreign universities and research institutions. International experts are invited to deliver lectures and guide student projects, while students are selected for exchange programs and internships abroad, broadening their international perspectives. Through the transformation of its talent cultivation model, the Shenzhen Research Institute of Tsinghua University has cultivated a large number of scientific and technological talents with innovative spirit and practical abilities, incubated numerous high-tech enterprises, and promoted industrial upgrading and innovative development in the Shenzhen region. Domestic scientific and technological talent cultivation should emphasize innovation education to foster students' innovation and entrepreneurship capabilities. Simultaneously, the resource advantages of universities and local regions should be fully utilized to build deeply integrated industry-university-research platforms that facilitate the transformation and application of scientific and technological achievements. Furthermore, creating an internationalized talent cultivation environment helps enhance students' global competitiveness.

5.2 Experience and Insights

The educational institution in this case has achieved remarkable results in operations and educational teaching. Its successful experience offers multifaceted reference value for other educational institutions. This institution has established a scientific and comprehensive curriculum system. Based on the cognitive characteristics and learning abilities of students of different age groups, courses are subdivided into multiple levels, each with clear teaching objectives and content. For example, for younger students, courses emphasize fun and foundational knowledge transmission, employing gamified and interactive teaching methods; for older students, theoretical depth and practical application content are increased. Simultaneously, the institution continuously updates course content to keep pace with educational frontiers and industry development trends. Regarding teacher training, it regularly organizes professional training and academic exchange activities for teachers, encouraging them to engage in teaching research and innovation. Other educational institutions should prioritize curriculum system development, implementing stratified teaching according to students' actual situations to meet the learning needs of different stages. Concurrently, they should monitor educational developments, promptly updating course content to ensure teaching timeliness and practicality. Additionally, strengthening teachers' professional development by providing training and exchange opportunities helps enhance teaching quality. This institution adopts a flat management model, reducing hierarchical layers to improve decision-making and execution efficiency. In resource allocation, human, material, and financial resources are reasonably distributed based on the actual needs of departments and projects, avoiding resource waste. Simultaneously, a comprehensive supervision and evaluation mechanism has been established, conducting regular assessments of teaching quality and employee performance to ensure the smooth implementation of all tasks. Educational institutions can optimize management structures, streamline processes, and improve operational efficiency[17]. Rational resource allocation and effective supervision and evaluation mechanisms ensure orderly execution of institutional tasks, enhancing overall operational standards. Other educational institutions may learn from this management model, adjusting and optimizing it according to their actual conditions.

Regarding enrollment, this educational institution employs diversified recruitment strategies, such as combining online and offline promotion methods, utilizing social media and offline events to attract potential students and parents. It also emphasizes communication and interaction with parents, regularly organizing parent meetings and open days to keep parents informed about students' progress and institutional developments. In student care, it provides personalized services such as psychological counseling and academic tutoring to enhance students' motivation and sense of belonging. Other educational institutions can adopt diversified enrollment strategies to broaden recruitment channels. Strengthening communication and interaction with parents establishes positive home-school cooperation relationships. Addressing students' personalized needs and providing attentive care services helps improve satisfaction and loyalty among students and parents. This educational institution focuses on shaping its brand image, building a strong brand reputation through unique educational philosophies and culture. In market promotion, it utilizes multiple channels for publicity, such as participating in education exhibitions and publishing high-quality educational content, thereby increasing its visibility and influence. Educational institutions should prioritize brand building, clarify their educational philosophies and characteristics, and conduct brand promotion through various channels to enhance brand recognition and reputation. A favorable brand image attracts more students and parents, laying a foundation for long-term institutional development.

6 CONCLUSION

This study systematically explores the objective inevitability and urgency of reshaping the competency structure of scientific and technological talents and transforming cultivation models in the era of artificial intelligence. The research finds that the AI era demands scientific and technological talents break through traditional disciplinary boundaries to construct a new competency structure centered on interdisciplinary knowledge integration, high-order innovation capabilities, continuous learning abilities, and critical and systemic thinking. Correspondingly, the cultivation model for scientific and technological talents urgently requires transformation toward content frontierization (integrating AI, data science, etc.), teaching practicization (project-based and inquiry-based learning), and diversified evaluation. Looking ahead, this study anticipates four major trends in scientific and technological talent cultivation: deep interdisciplinary integration, equal emphasis on practice and innovation, expansion of international perspectives, and personalized pathway customization. Key challenges requiring resolution include constructing interdisciplinary models, deepening AI-empowered education, optimizing internationalization strategies, and scientifically evaluating innovation capabilities. To address these, collaborative advancement is recommended through policy guidance and support, deepened school-enterprise collaboration, strengthened faculty development, and fostering an innovation culture. This study contends that successfully reshaping the competency structure of scientific and technological talents and realizing the transformation of cultivation models hold crucial strategic significance for enhancing individuals' competitiveness in the AI wave, driving national scientific and technological innovation and high-quality development, and ultimately achieving scientific and technological self-reliance while contributing to human progress.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3057

COORDINATED DEVELOPMENT OF CROSS-BORDER E-COMMERCE INDUSTRY AND STRATEGIC EMERGING INDUSTRIES IN JIANGXI PROVINCE

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Abstract: This study, set against the backdrop of Jiangxi Province's' 1269 'Action Plan, explores the pathways and mechanisms for integrating the cross-border e-commerce industry with strategic emerging industries. In the context of the rapid development of the global digital economy and the formation of a dual circulation pattern both domestically and internationally, cross-border e-commerce, as a new form of trade, has formed deep interactions with Jiangxi Province's key strategic emerging industries, such as electronics, new energy, and aviation. The study employs methods such as literature analysis, data mining, and case studies to systematically examine the current status, collaborative mechanisms, and integration paths of the cross-border e-commerce industry and strategic emerging industries in Jiangxi Province. The findings indicate that Jiangxi Province has effectively promoted the digital transformation of traditional industries and the international layout of emerging industries through the 'cross-border e-commerce + industrial belt' model, forming distinctive cross-border e-commerce industrial belts in areas like Ganzhou furniture, Jingdezhen ceramics, and Nanchang electronics. However, there are still shortcomings in policy coordination, industrial chain integration, and talent support. This study proposes a 'four-dimensional linkage' model of coordinated development, providing a theoretical framework and practical reference for inland regions to leverage cross-border e-commerce to empower industrial upgrading.
Keywords: Cross-border e-commerce; Strategic emerging industry; Industrial coordination; Digital transformation

1 INTRODUCTION

In the context of the restructuring of global value chains and the thriving digital economy, cross-border e-commerce has become a key driver for transforming China's foreign trade and upgrading its industries[1]. According to data from the Ministry of Commerce, in 2024, China's cross-border e-commerce import and export volume reached 2.63 trillion yuan, marking a 10.8% year-on-year increase, with a growth of over ten times over the past five years. The rapid development of this new trade model is profoundly altering the internationalization paths and models of traditional industries. Meanwhile, provinces and cities are increasingly focusing on strategic emerging industries as the core drivers of high-quality economic development. How to leverage cross-border e-commerce to support the international layout of these strategic emerging industries has become a critical issue for regional economic development[2].

As an inland open economy experimental zone, Jiangxi Province has made significant progress in the development of strategic emerging industries under the guidance of the '1269' action plan in recent years. In 2024, the province's electronic information industry revenue surpassed 1.16 trillion yuan, marking the third consecutive year it has reached this milestone. The added value of large-scale industrial enterprises grew by 8.5%, ranking fifth in the country[3]. Notably, Jiangxi's cross-border e-commerce sector has seen explosive growth, with a total import and export volume of 127.52 billion yuan in 2022, placing it fifth nationally and first in the central and western regions, fostering a positive interaction with the strategic emerging industries[4].

In this context, exploring the synergistic development mechanism between the cross-border e-commerce industry and Jiangxi Province's strategic emerging industries holds significant theoretical and practical importance[5]. Theoretically, most existing research focuses on the integration of cross-border e-commerce with traditional manufacturing or the technological innovation pathways of strategic emerging industries, while studies on how cross-border e-commerce can empower the internationalization of these industries are relatively scarce. Practically, as an inland province, Jiangxi Province, under the geographical condition of being neither coastal nor bordering, has achieved a leapfrog development through the synergy of cross-border e-commerce and strategic emerging industries, which offers valuable lessons for similar regions[6].

This study is grounded in the implementation of Jiangxi Province's' 1269 'Action Plan and the development of a modern industrial system. It systematically examines the interaction, coordination mechanisms, and integration paths between the cross-border e-commerce industry and strategic emerging industries, focusing on the following questions: (1) the current status and characteristics of the cross-border e-commerce industry and strategic emerging industries in Jiangxi Province; (2) the coordination mechanisms and effects between these two sectors; (3) practical experiences and existing issues with the' cross-border e-commerce + industrial belt' model in Jiangxi Province; (4) policy recommendations and implementation strategies to promote the deep integration of these two industries[7].

2 DEVELOPMENT STATUS OF CROSS-BORDER E-COMMERCE INDUSTRY AND STRATEGIC EMERGING INDUSTRIES IN JIANGXI PROVINCE

2.1 The Rise and Characteristics of Cross-Border E-Commerce Industry in Jiangxi Province

Although the cross-border e-commerce industry in Jiangxi Province started late, it has grown rapidly and developed distinct inland characteristics. In terms of scale, the total import and export value of cross-border e-commerce in the province reached 127.52 billion yuan in 2022, and continued to grow rapidly in 2023[8]. Notably, Ganzhou City's' 1210 'cross-border e-commerce online shopping bonded import business volume surpassed ten million orders, with an import value of 483 million yuan. In terms of spatial layout, the province has formed a development pattern with Nanchang and Ganzhou as the dual cores, supported by multiple points such as Jingdezhen and Ji' an. Nanchang, leveraging its advantages in the electronics information industry, saw its cross-border e-commerce import and export value reach 20.4 billion yuan in 2023[9]. Ganzhou, based on its furniture industry belt, saw its cross-border trade goods import and export volume exceed 45 million tickets, driving foreign trade to surpass 10 billion yuan for two consecutive years[10].
The development of cross-border e-commerce in Jiangxi province shows three significant characteristics:
The industrial belt drives the development of cross-border e-commerce in Jiangxi Province. Unlike the coastal areas, where platform enterprises dominate, Jiangxi's cross-border e-commerce primarily relies on local industrial belts, forming a unique' cross-border e-commerce + industrial belt 'model[11]. The Nankang furniture industry belt in Ganzhou has expanded its market to over 100 countries and regions through cross-border e-commerce, boosting the industry's scale to over 270 billion yuan. The Jingdezhen ceramic industry belt has developed a number of platform enterprises targeting the global market through the construction of cross-border e-commerce comprehensive pilot zones. Nanchang, leveraging its electronic information industry, has strengthened cooperation with major e-commerce platforms. This industrial belt-driven model ensures that Jiangxi's cross-border e-commerce has a solid industrial foundation and sustained innovation momentum.
Logistics channels have significant advantages. Jiangxi Province has leveraged its 'well-connected' geographical advantages to establish an efficient and convenient international logistics network. On one hand, through platforms such as the Ganzhou International Land Port and Nanchang Airport, it has formed major international logistics routes that extend south, east, north, and west. On the other hand, by innovating the 'cross-border e-commerce + China-Europe train + overseas warehouse' model, it has effectively addressed the cross-border logistics challenges for large items like furniture. Through this model, Nankang District has successfully exported furniture to over 100 countries and regions worldwide[12].
Policy innovation continues to deepen. Jiangxi Province has integrated cross-border e-commerce into the '1269' action plan, introducing a series of supportive policies. These include setting up a special fund for cross-border e-commerce development, optimizing tax policies, and enhancing financial service innovations. Cities like Ganzhou and Nanchang are also exploring regulatory innovations, such as the 'four-zone integration' model (international land port, comprehensive bonded zone, cross-border e-commerce comprehensive pilot zone, and import trade promotion and innovation demonstration zone) introduced by Ganzhou, which has significantly improved trade facilitation[13].

2.2 Layout and Achievements of Strategic Emerging Industries in Jiangxi Province

Jiangxi Province's 14th Five-Year Plan clearly proposes to build an industrial space pattern of "one core, two wings and multiple bases", focusing on the development of six strategic emerging industries and seven digital economy industries. After years of cultivation, the development of strategic emerging industries has achieved remarkable results.
The electronic information industry, as Jiangxi Province's first trillion-yuan-level industry, has developed into an industrial cluster belt centered around the Jingjiu High-Speed Railway. In 2024, it generated a revenue of 1.16 trillion yuan, accounting for 20.9% of the province's large-scale industrial revenue and contributing 34.2% to industrial growth[14]. Nanchang focuses on semiconductor lighting and smart terminals; Ji'an develops communication terminals and electronic components; Jiujiang and Ganzhou focus on new electronic materials and printed circuit boards; Shangrao, Yichun, and Yingtan concentrate on photovoltaic, lithium batteries, and the Internet of Things, forming a relatively complete industrial chain[15].
The new energy industry, primarily focused on lithium batteries and photovoltaics, has formed industrial clusters in cities such as Shangrao, Yichun, and Xinyu. Yichun, leveraging its abundant lithium ore resources, has established itself as the 'Lithium Capital of Asia,' with the lithium battery industry chain continuously expanding. Meanwhile, Shangrao's photovoltaic sector is growing steadily, and Jinko Solar, a leading company, has become a global leader in photovoltaic module shipments.
As shown in table 1, the aviation industry, supported by Nanchang Aviation City and Jingdezhen Aviation Town, has developed a comprehensive industrial chain that includes trainer aircraft, helicopters, and drones. Nanchang Aviation City is home to leading enterprises such as Hongdu Aviation and the China Commercial Aircraft Corporation Jiangxi Production and Test Flight Center, while Jingdezhen focuses on the helicopter sector. Together, these two cities are working to realize Jiangxi's' aviation dream.'

Table 1 Layout and Scale of Major Strategic Emerging Industries in Jiangxi Province (2024)

estate / class	Key layout area	Main segments	Industry scale	Represents enterprise/project
electronic information	Nanchang, Ji 'an, Ganzhou, Jiujiang	Semiconductor lighting, intelligent terminal, electronic components	one trillion, one hundred and sixty billion yuan	Ofei Optoelectronics, Mulinsen Lighting
new energy	Shangrao, Yichun, Xinyu	Photovoltaic, lithium and hydrogen energy	-	Jinko Solar, Ganfeng Lithium
aviation	Nanchang, Jingdezhen	Coaches, helicopters, drones	-	Hongdu Aviation, Changhe Aircraft
new material	Yingtan, Ganzhou, Nanchang	Copper based, tungsten based and rare earth materials	-	Jiangxi Copper, China Rare Earth Group
traditional Chinese medicine	Zhangshu, Nanchang	Chinese medicine manufacturing, Chinese medicine services	-	Renhe Pharmaceutical, Jiangzhong Group
digital economy	Nanchang, Yingtan, Shangrao	VR, Internet of Things, big data	The added value accounted for more than 45% of GDP	Nanchang VR Industry Base

2.3 The Internal Connection between Cross-Border E-Commerce and Strategic Emerging Industries

Cross-border e-commerce and strategic emerging industries are not isolated in Jiangxi's economic development; instead, they have formed a deep interactive relationship. On one hand, cross-border e-commerce provides a fast track for the international development of strategic emerging industries; on the other hand, these industries supply high-quality products and drive innovation for cross-border e-commerce.

Cross-border e-commerce is empowering the internationalization of strategic emerging industries. Under traditional trade models, the internationalization of emerging industries faces challenges such as long channel construction periods and high costs. Cross-border e-commerce, through digital platforms, significantly lowers the barriers for companies to enter the international market. For instance, in Ganzhou's electronic information industry, products like printed circuit boards and electronic components produced locally can now directly connect with global buyers via cross-border e-commerce platforms, thereby shortening the supply chain. In Nanchang, LED lighting products have achieved annual exports exceeding 5 billion yuan through cross-border e-commerce, reaching over 120 countries and regions.

Strategic emerging industries enhance the competitiveness of cross-border e-commerce. Unlike traditional cross-border e-commerce products such as clothing and daily necessities, strategic emerging industry products are characterized by high technological content and added value, which can boost the profit margins and brand influence of cross-border e-commerce. For instance, in Jiangxi's electronic information sector, products like smart terminals and semiconductor lighting have an average export price 3 to 5 times higher than traditional products. The furniture industry in Ganzhou has successfully expanded its brand presence overseas through cross-border e-commerce, significantly enhancing the premium pricing power of its products.

Digital technology and cross-border e-commerce mutually reinforce each other. The key digital industries in Jiangxi Province, such as VR, IoT, and big data, provide essential technical support for cross-border e-commerce. In Nanchang, VR technology is used to enhance user experience by showcasing and marketing products for cross-border e-commerce. In Yingtan, IoT technology optimizes logistics tracking and warehouse management for cross-border e-commerce. Conversely, the growth of cross-border e-commerce also provides practical applications and market opportunities for digital technology, driving technological innovation and upgrades.

3 THE MECHANISM AND EFFECT OF CROSS-BORDER E-COMMERCE AND STRATEGIC EMERGING INDUSTRIES DEVELOPING IN SYNERGY

3.1 The Theoretical Basis of Coordinated Development

The coordinated development of cross-border e-commerce industry and strategic emerging industries can be explained from three dimensions: industrial integration theory, global value chain theory and innovation ecosystem theory.

According to the theory of industrial integration, different industries or sectors within the same industry can form new industries through mutual penetration and cross-fusion. In the context of the digital economy, cross-border e-commerce, as a new form of trade, is increasingly integrating with strategic emerging industries in terms of technology, products, and markets. The 'cross-border e-commerce + industrial belt' model in Jiangxi Province essentially represents the integration of trade digitalization and industrial upgrading, giving rise to new business models and value creation methods.

The theory of global value chains highlights that companies or regions can achieve industrial upgrading and technological advancement by participating in the global value chain. Cross-border e-commerce reduces intermediary links, enabling enterprises in strategic emerging industries in inland areas to directly connect with the global market, transforming from passive recipients to active participants, and even becoming 'chain leaders' in the value chain. The furniture industry in Ganzhou has gradually shifted from OEM contract manufacturing to ODM design and manufacturing, and then to OBM brand manufacturing through cross-border e-commerce platforms, continuously enhancing its position in the global value chain.

The theory of the innovation ecosystem views regional economic development as an ecosystem comprising various innovative entities and environments. In this system, cross-border e-commerce platforms, strategic emerging industry enterprises, research institutions, and government departments interact to form a network for knowledge flow and innovation diffusion. Jiangxi Province has promoted the aggregation and circulation of innovative elements by establishing comprehensive cross-border e-commerce pilot zones and industrial innovation alliances, thereby providing sustained innovation momentum for strategic emerging industries.

3.2 The Mechanism of Coordinated Development

The coordinated development of cross-border e-commerce and strategic emerging industries is mainly realized through the following mechanisms:

Market expansion mechanism. Cross-border e-commerce has broken the time and space constraints of traditional trade, providing new channels for strategic emerging industries to access the global market. Especially for technology-intensive products like electronics and new materials, traditional foreign trade channels often face challenges such as certification difficulties and high promotion costs. However, cross-border e-commerce platforms significantly reduce these costs through precise matching and digital marketing. According to statistics, enterprises in Jiangxi Province's strategic emerging industries can reduce their international market expansion costs by about 40% compared to traditional methods, while improving efficiency by over 50%.

Innovative feedback mechanism. Cross-border e-commerce platforms have accumulated a vast amount of international market data and consumer feedback, which serves as a crucial basis for product innovation in strategic emerging industries. By analyzing the sales data and user reviews from these platforms, companies can accurately gauge changes in international market demand and promptly adjust their product design and R&D strategies. For instance, a furniture company in Ganzhou noticed through cross-border e-commerce platform feedback that the demand for eco-friendly furniture in the European and American markets was rapidly increasing. The company then adjusted its materials and production processes to develop a series of eco-friendly furniture products, successfully entering the high-end market.

The mechanism for integrating elements. The growth of cross-border e-commerce has facilitated the cross-border flow and optimal allocation of high-end resources, including talent, technology, and capital. On one hand, cross-border e-commerce platforms have attracted a significant number of international talents and advanced technologies; on the other hand, the development of strategic emerging industries also requires these high-end resources. Jiangxi Province has leveraged its cooperation with the Guangdong-Hong Kong-Macao Greater Bay Area through cross-border e-commerce to introduce advanced experiences and talent resources in electronic information technology and logistics management from places like Shenzhen. Additionally, the foreign exchange earnings and capital accumulation generated by cross-border e-commerce have provided financial support for the technological research and development and equipment upgrades of strategic emerging industries.

Brand enhancement mechanism. Under the traditional trade model, it is challenging for inland enterprises to establish their own international brands. However, cross-border e-commerce, through digital marketing and social media, has opened up new avenues for brand building. Industries in Jiangxi Province, such as electronics and furniture, have leveraged cross-border e-commerce platforms to nurture a number of internationally recognized brands. For instance, Nankang Furniture has set up brand stores on platforms like Amazon and Shopee, with products reaching over 20 countries and regions, including Europe, America, and Southeast Asia, significantly enhancing its brand premium.

3.3 Economic Effects of Coordinated Development

The coordinated development of cross-border e-commerce and strategic emerging industries has produced significant economic effects, which are mainly reflected in the following aspects:

The industrial structure upgrade effect. Cross-border e-commerce, guided by market demand, has driven Jiangxi Province's industrial structure to upgrade towards high technology and high value-added sectors. On one hand, traditional industries, after connecting with the global market through cross-border e-commerce, have had to enhance their product technology content and quality standards to compete internationally. On the other hand, the market opportunities provided by cross-border e-commerce have attracted more resources to strategic emerging industries such as electronics and new energy. Data shows that in 2024, the added value of strategic emerging industries in Jiangxi Province accounted for 25% of the GDP, an increase of 7 percentage points from 2020.

The optimization of the trade structure has been significantly influenced by cross-border e-commerce, which has transformed Jiangxi Province's export structure from primarily resource-based products and primary manufactured goods to a more diversified mix, with a growing share of high-tech exports. In 2023, the export ratio of electromechanical products and high-tech products in Jiangxi Province reached 45.2% and 28.6%, respectively, representing increases of 12.3 and 9.8 percentage points compared to 2020. Notably, the rapid growth in the export of electronic information products through cross-border e-commerce has become a new driver of foreign trade growth. The annual average growth rate of cross-border e-commerce exports of electronic information products in Nanchang High-tech Zone exceeds 30%, significantly outpacing the growth rate of traditional product exports.

The agglomeration effect of industries. The interaction between cross-border e-commerce and strategic emerging industries has facilitated the formation and development of industrial clusters. On one hand, cross-border e-commerce companies tend to cluster in regions with a solid industrial foundation; on the other hand, enterprises in strategic emerging industries also prefer to locate in areas with well-developed cross-border e-commerce services. Jiangxi

Province has developed several distinctive cross-border e-commerce industry clusters, such as Nanchang's electronics information, Ganzhou's furniture, and Jingdezhen's ceramics, which have generated significant economies of scale and scope. For instance, the rapid growth of the cross-border e-commerce sector in Ganzhou's furniture industry has attracted over 900 related enterprises, forming a complete industrial chain from design, manufacturing, marketing, to logistics.

The improvement in employment quality. The integration of cross-border e-commerce with strategic emerging industries has created numerous high-skilled and high-paying jobs. On one hand, the operation of cross-border e-commerce requires professionals in e-commerce operations, digital marketing, and international logistics; on the other hand, the growth of strategic emerging industries has increased the demand for high-end positions in research and development, design, and management. According to statistics, over 1 million people in Jiangxi Province are employed in cross-border e-commerce and strategic emerging industries, with more than 60% holding a college degree or higher, and their average salary is over 30% higher than that of traditional industries.

4 PRACTICE EXPLORATION OF "CROSS-BORDER E-COMMERCE + INDUSTRIAL BELT" MODEL IN JIANGXI PROVINCE

4.1 Ganzhou Furniture Industry Belt: a Model of Digital Transformation of Traditional Industries

Nankang District, known as the 'Capital of Chinese Solid Wood Furniture,' has achieved a digital transformation and international upgrade of its traditional furniture industry through cross-border e-commerce, serving as a prime example of the 'cross-border e-commerce + industrial belt' development in inland regions. Nankang District has embraced cross-border e-commerce as a key driver for the transformation and upgrading of the furniture industry, actively exploring new opportunities in this emerging market. In 2023, the district's cross-border trade volume surpassed 45 million transactions, driving foreign trade to exceed 10 billion yuan for two consecutive years and boosting the furniture industry's scale to over 270 billion yuan.

The core of the Nankang model is to establish a comprehensive cross-border e-commerce ecosystem. On the production side, it promotes digital transformation in furniture companies by building shared intelligent material preparation centers and innovative design centers, enhancing product standardization and design innovation. On the distribution side, it collaborates deeply with platforms like Alibaba International and Amazon, constructing cross-border e-commerce industrial parks and overseas warehouses to build an international marketing network that reaches directly to consumers. On the service side, it introduces professional institutions such as the Shenzhen Cross-border E-commerce Association to provide comprehensive services including talent development, brand building, and supply chain optimization. Through this ecosystem, Nankang furniture has transformed from 'offline wholesale' to 'brand going global,' increasing its average profit margin from 8% to over 20%.

Notably, Nankang District has innovatively developed the ' cross-border e-commerce + China-Europe train + overseas warehouse ' model, effectively addressing the logistics challenges of large furniture items. Through the Ganzhou International Land Port China-Europe Train, furniture products can reach major markets in Europe and Central Asia directly, reducing logistics time by two-thirds compared to sea freight and cutting costs by 40%. Additionally, overseas warehouses have been established in key target markets to facilitate localized storage and distribution, significantly enhancing the consumer experience. Currently, Nankang furniture is exported to over 100 countries and regions worldwide, with timber imported from more than 70 countries and regions, creating a 'buy globally, sell globally' market.

4.2 Nanchang Electronic Information Industry Belt: Technology-Driven Cross-Border E-Commerce Development Path

Nanchang City, as the core area of Jiangxi Province's electronic information industry, has explored a technology-driven path for cross-border e-commerce development. In 2023, Nanchang's total cross-border e-commerce import and export volume reached 20.4 billion yuan, with over 60% of the products being electronic information products. Unlike the furniture industry belt in Ganzhou, the products from Nanchang's electronic information industry belt are characterized by high technological content and rapid updates, which places higher demands on the supply chain response speed and intellectual property protection in cross-border e-commerce.

The core of the Nanchang model lies in the establishment of a collaborative system that integrates technology research and development, cross-border e-commerce, and digital services. In terms of technology R&D, the model leverages platforms such as the Nanchang High-tech Zone and the Nanchang Economic and Technological Development Zone to attract leading enterprises like O-Film and Jingneng Optoelectronics, forming a comprehensive industrial chain from LED chips, packaging, to applications. For cross-border e-commerce, the focus is on developing a B2B model, collaborating with global electronic component distribution platforms to establish direct channels for international buyers. In digital services, the model utilizes technologies such as VR and big data to create systems for virtual product displays, intelligent supply-demand matching, and online technical support. This approach enables Nanchang's electronic information products to swiftly adapt to changes in international market demands, maintaining a technological edge.

The Nanchang Electronic Information Industry Belt is also actively exploring the integration and innovation of cross-border e-commerce with digital technologies. On one hand, VR technology is being used to enhance the online display of electronic components and smart devices through virtual exhibition halls and 3D product models. On the other hand, IoT technology is being utilized to optimize cross-border logistics, enabling full-process tracking and intelligent warehouse management. These innovations not only boost the operational efficiency of cross-border e-commerce but also promote the commercial application of digital technologies like VR and IoT, creating a virtuous cycle.

4.3 Jingdezhen Ceramic Industry Belt: Cultural Empowerment of Cross-Border E-Commerce Brand Construction

Jingdezhen City is leveraging its cultural heritage as the 'Thousand-Year Porcelain Capital' to promote the high-end development of the ceramics industry and internationalize its brands through cross-border e-commerce. In 2022, Jingdezhen was designated as a national cross-border e-commerce comprehensive pilot zone, leading to a significant increase in the export value of ceramic products via cross-border e-commerce. It is projected that by 2025, this value will reach over 10 billion yuan.

The essence of the Jingdezhen model lies in cultural empowerment and brand enhancement. On one hand, it involves deeply exploring the cultural significance of ceramics, integrating traditional techniques with modern design to create ceramic products that are both culturally rich and aesthetically appealing. On the other hand, it leverages cross-border e-commerce platforms for cultural promotion and brand marketing to boost the international recognition of the 'Jingdezhen' brand. Companies like Jingdezhen Ceramic Expo City Cross-border Trade Comprehensive Service Co., Ltd. offer a range of services, including brand incubation and intellectual property protection, to support small and medium-sized ceramic enterprises in transitioning from contract manufacturing to brand management.

Jingdezhen also focuses on building a cross-border e-commerce ecosystem for ceramics. By introducing and nurturing cross-border e-commerce platforms, it provides ceramic companies with channels for external communication and marketing. It organizes brand enterprises to establish overseas warehouses, enabling localized operations and services. Additionally, it collaborates with renowned art schools both domestically and internationally to train versatile talents who are proficient in both ceramic art and e-commerce operations. This ecosystem ensures that Jingdezhen's ceramic industry maintains its cultural identity while successfully integrating into the global market.

4.4 Challenges to Coordinated Development

Although the "cross-border e-commerce + industrial belt" model in Jiangxi province has achieved remarkable results, it still faces many challenges in the process of deep integration between cross-border e-commerce and strategic emerging industries:

Policy coordination is insufficient. Cross-border e-commerce and strategic emerging industries are managed by different departments, including commerce, industry and information technology, and science and technology, making policy coordination challenging. Most existing support policies are general, lacking specific support for cross-border e-commerce of technology products. For example, issues such as testing and certification, and intellectual property protection in the export of high-tech products through cross-border e-commerce have not yet been systematically addressed.

The industrial chain is not fully developed. Jiangxi Province's cross-border e-commerce service chain still has shortcomings, particularly in high-end areas such as international logistics, payment settlement, and digital marketing. For instance, the demand for the timeliness and stability of cross-border logistics is extremely high for electronic information products, but Jiangxi's limited international air cargo capacity hinders the industry's development.

There is a shortage of talent in the structural level. The coordinated development of cross-border e-commerce and strategic emerging industries requires professionals who are proficient in both technical expertise and international trade, but Jiangxi Province faces a severe shortage of such talents. Although the province trains nearly 10,000 e-commerce professionals annually, it still heavily relies on recruiting high-end operational talents and cross-border e-commerce data analysts from coastal regions.

The brand influence is limited. In addition to traditional competitive products such as furniture and ceramics, the brand awareness of strategic emerging industrial products in Jiangxi province in the international market is not high, mainly through cross-border e-commerce platforms to sell at low prices or contract manufacturing for international brands, and the construction of independent brands has a long way to go.

The development of data elements is insufficient. Cross-border e-commerce platforms have accumulated a vast amount of international market data, but these data resources have not been fully transformed into industrial innovation elements. On one hand, the data sharing mechanism is inadequate; on the other hand, companies' capabilities in data analysis and application are limited, making it difficult to extract value from the data.

5 CONCLUSION AND DISSCUSSION

5.1 Construction of "Four-Dimensional Linkage" Coordinated Development Model

Based on the practice of Jiangxi province and the law of industrial development, this study puts forward a "four-dimensional linkage" model for the coordinated development of cross-border e-commerce and strategic emerging industries, including four dimensions: industrial empowerment, innovation drive, ecological co-construction and

institutional guarantee.
The dimension of industrial empowerment highlights the role of cross-border e-commerce as a new type of infrastructure, offering comprehensive support to strategic emerging industries in market expansion, brand building, and supply chain optimization. Specific strategies include: developing specialized cross-border e-commerce platforms for specific sectors like electronics and information technology, and new energy, to provide professional services; promoting the B2B model of cross-border e-commerce to facilitate direct connections between strategic emerging industry enterprises and global buyers; and establishing a 'cross-border e-commerce + overseas warehouse' network to enhance the international service capabilities for high-tech products.
The innovation drive highlights the interaction between cross-border e-commerce and strategic emerging industries in technological, model, and business innovation. Key measures include: establishing a big data center for cross-border e-commerce to support industrial innovation; promoting the use of VR/AR technology in product display and marketing; exploring the application of blockchain technology in cross-border e-commerce payments and logistics tracking to enhance transaction security and efficiency.
The dimension of ecological co-construction focuses on building a collaborative network involving multiple stakeholders, including enterprises, platforms, service providers, and research institutions. Key measures include: developing a 'garden within a garden' model that integrates cross-border e-commerce parks with strategic emerging industry bases; cultivating comprehensive cross-border e-commerce service providers to offer full-chain services to strategic emerging industries; forming industrial innovation alliances to promote collaborative innovation among industry, academia, and research.
As shown in table 2, the institutional guarantee dimension focuses on the construction of support systems, including policy coordination, standard setting, and talent development. Key tasks include: establishing a cross-departmental coordination mechanism to integrate policies for the development of cross-border e-commerce and strategic emerging industries; formulating standards for cross-border e-commerce transactions of technical products, covering product classification, quality assessment, and after-sales service; and enhancing the cross-border e-commerce talent training system to cultivate versatile professionals.

Table 2 Key Areas and Paths for the Coordinated Development of Cross-Border E-Commerce and Strategic Emerging Industries in Jiangxi Province

estate / class	Key points of coordinated development	Cross-border e-commerce empowerment path	Expected results
electronic information	Smart terminal, semiconductor lighting, automotive electronics	Industry vertical platform, digital marketing, technical support	Increase international market share and enhance brand influence
new energy	Photovoltaic modules, lithium products, energy storage systems	B2B cross-border e-commerce, green certification, EPC services	Expand the "Belt and Road" market and promote green products to go overseas
aviation	Drones, aviation parts, simulators	Technology trade, service trade, digital display	Promote international cooperation in aviation technology and open up new markets
new material	Copper based materials, rare earth functional materials	Cross-border supply chain e-commerce, technical standards output	Improve the added value of the material industry and master the pricing power
traditional Chinese medicine	Chinese medicine preparation, health care products, Chinese medicine equipment	Cross-border retail, cultural communication and service export	Promote the internationalization of TCM and spread Chinese culture
digital economy	VR/AR, Internet of Things, big data	Digital service export, technical solutions	We will foster new advantages in digital trade and seize the commanding heights

5.2 Specific Paths for Industrial Synergy Upgrading

As the first trillion-yuan industry in Jiangxi Province, the electronic information industry should focus on three key areas for its coordinated development with cross-border e-commerce: First, prioritize the B2B model of cross-border e-commerce for products like semiconductor lighting and smart terminals. By collaborating with global electronic component distribution platforms, establish a stable international supply chain. Second, use data from cross-border e-commerce to guide product innovation, such as adjusting R&D directions based on changes in international demand for smart home devices. Third, promote technical standards through cross-border e-commerce platforms to enhance the industry's international influence.
The key points of the collaboration between the new energy industry and cross-border e-commerce include: first, establishing a green certification and international promotion system for products such as photovoltaic and lithium batteries, using cross-border e-commerce platforms to convey environmental values and enhance product premium;

second, developing an 'e-commerce + EPC service' model to provide comprehensive solutions, including photovoltaic power stations and energy storage systems, to countries along the 'Belt and Road' route; third, building a big data platform for cross-border e-commerce in the new energy sector to monitor global market demand and technological trends in real time.

The synergy between the aviation industry and cross-border e-commerce is unique, with a focus on: first, developing cross-border e-commerce exports of drones and related services, leveraging platforms to precisely connect with international buyers; second, promoting trade in aviation technology and services through cross-border e-commerce, such as exporting flight simulator technology and providing pilot training services; third, using VR/AR technology for the digital display and marketing of aviation products, enhancing user experience.

The synergy between the traditional Chinese medicine (TCM) industry and cross-border e-commerce holds significant potential. This can be achieved through the following approaches: 1) developing cross-border retail of TCM preparations and health products to directly reach overseas consumers; 2) promoting TCM culture on cross-border e-commerce platforms to enhance international recognition; 3) exploring a 'cross-border e-commerce + TCM services' model to promote the internationalization of TCM diagnostic and wellness services.

5.3 Policy Innovation and Safeguard Measures

In order to promote the deep coordination between cross-border e-commerce and strategic emerging industries, Jiangxi province should further improve the policy system and safeguard measures:

Strengthen top-level design and policy coordination. It is recommended to establish a provincial leadership group for the coordinated development of cross-border e-commerce and strategic emerging industries, to coordinate resources from various departments such as commerce, industry and information technology, science and technology, and customs, and to formulate specialized development plans and supporting policies. Key areas include: establishing a special fund for the coordinated development of cross-border e-commerce and industrial innovation; formulating facilitation measures for the export of high-tech products through cross-border e-commerce; improving the data sharing mechanism for cross-border e-commerce to provide data support for industrial innovation.

Improve the industrial chain support service system. To meet the specific needs of cross-border e-commerce for strategic emerging industry products, establish a specialized service system: set up high-tech product testing and certification platforms to provide international certification services; develop cross-border intellectual property services to assist companies in international patent layout and protection; enhance the international logistics system, particularly by strengthening air cargo capacity, to meet the transportation needs of high-value, time-sensitive products.

To address the shortage of versatile talents, a multi-faceted approach is needed to innovate and introduce talent mechanisms. This includes promoting universities to offer 'major + cross-border e-commerce' interdisciplinary programs, such as dual degrees in 'electronic information engineering + international trade'; establishing practical training bases for cross-border e-commerce and industrial innovation talents to conduct real-world training; implementing a high-end talent introduction plan to attract professionals in cross-border e-commerce platform operations and international digital marketing; and establishing a talent cooperation mechanism with the Guangdong-Hong Kong-Macao Greater Bay Area to share talent resources.

Deepen international cooperation and align with global rules. Seize the opportunity of 'Belt and Road' construction to expand international cooperation: establish cross-border e-commerce cooperation mechanisms with major trading partners, promoting mutual recognition of product standards; participate in the formulation of international digital trade rules to enhance our influence; encourage enterprises to engage in the restructuring of the international industrial chain through cross-border e-commerce, integrating into the global value chain at a higher level.

Optimizing the business environment and risk management. To foster a favorable environment for coordinated development: improve the statistical monitoring system for cross-border e-commerce to promptly track industry trends; establish a risk warning and response mechanism for cross-border e-commerce to prevent risks such as international trade frictions and intellectual property disputes; strengthen the integrity system of cross-border e-commerce to maintain a fair competitive environment.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

FUNDING

This project is funded by the Jiangxi Provincial Social Science Fund Project "Research on the Development of Strategic Emerging Industry Integration Clusters in Jiangxi Province", project number: 23WT78.

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3058

INTERNAL CONTROLS, GOVERNANCE STRUCTURES, AND FINANCIAL RISK: A TRIADIC ANALYSIS IN LISTED COMPANIES

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Abstract: In today's highly dynamic and complex business environment, the intrinsic relationship among internal control, governance structure, and financial risk in listed companies has drawn significant attention. Serving as the cornerstone for ensuring operational effectiveness and financial information reliability, internal control works in close synergy with the corporate governance structure, collectively forming the enterprise governance framework. As financial risk represents a core threat to companies, mitigating it effectively depends critically on robust internal control mechanisms and efficient governance structures. Consequently, in-depth research into the interplay among these three elements in listed companies holds substantial practical value for enhancing operational efficiency, strengthening financial transparency, and reducing overall risk.
Keywords: Listed companies; Internal control; Corporate governance structure; Financial risks

1 INTRODUCTION

The intrinsic relationship among internal control, governance structure, and financial risk in listed companies constitutes a fundamental pillar for corporate sustainability and stable operations. Amid deepening financial market evolution and escalating regulatory requirements, enhancing internal control systems and optimizing governance frameworks have emerged as strategic imperatives in corporate management[1]. This study methodically examines the interactive mechanisms between these three elements, elucidating their dynamic interplay pathways. The research aims to provide executives with forward-looking decision-making support and risk mitigation strategies, while contributing both theoretical insights and practical guidance for advancing governance efficacy, strengthening internal control quality, and reducing financial exposures.

2 MITIGATING EFFECTS OF INTERNAL CONTROL SYSTEMS AND GOVERNANCE STRUCTURES

2.1 Enhance the Transparency of Enterprise Financial Information

Listed companies operate in intensely competitive and rapidly evolving markets, confronting multidimensional risks including market volatility, credit defaults, and liquidity pressures. Such exposures may jeopardize operational continuity, financial stability, and corporate reputation, potentially triggering insolvency. Mitigating these threats necessitates establishing comprehensive internal control systems and effective governance frameworks[2].

The persistence of financial risk underscores the critical role of internal controls. As institutional safeguards for achieving operational objectives, protecting assets, and ensuring financial information reliability, robust internal controls enable systematic identification, assessment, and management of financial exposures[3]. This enhances the credibility of financial reporting and operational transparency while optimizing resource efficiency and risk resilience. Listed companies thereby safeguard stakeholder interests, maintain developmental stability, and prevent potential risk incidents.

Financial risk equally highlights the strategic significance of governance structures. By defining decision-making hierarchies and constructing oversight mechanisms, governance frameworks ensure governing bodies (shareholder meetings, boards of directors) exercise lawful supervision, prompting management to conduct prudent operations. When financial risks materialize, efficient governance architectures drive collaborative responsibility between governing bodies and management. Timely interventions preserve financial resilience, contain risk contagion, and protect corporate/investor interests.

Fundamentally, financial risk exhibits profound interdependency with internal controls and corporate governance. Mature control systems and governance frameworks jointly empower full-cycle risk management, fortifying operational foundations while enhancing disclosure quality and market competitiveness. Listed companies must prioritize risk governance, continuously refining internal controls and governance systems to navigate market disruptions and achieve sustainable value creation.

2.2 Assessing the Execution of Internal Controls for Financial Risks

Sector-specific variations in market competition, regulatory intensity, and business models fundamentally shape the design and implementation of internal control and governance frameworks, creating distinct requirements across industries and company scales. Financial institutions, for instance, demand rigorous control mechanisms to navigate complex risk exposures, while technology enterprises rely on flexible governance structures to preserve innovation agility and market responsiveness. Organizationally, large corporations with multifaceted operations necessitate robust risk management systems, whereas resource-constrained SMEs may adopt streamlined governance approaches.

Establishing evaluation systems for operational resilience requires integrating the core risk management functions of controls and governance with their interdependencies across business operations and financial ecosystems, thereby developing multidimensional assessment criteria. Control evaluations must balance design rationality with implementation efficacy, prioritizing the integrity of risk prevention mechanisms, structural soundness and operational efficiency of governance, alongside information disclosure quality and board oversight effectiveness.

Corporate assessment frameworks should incorporate risk correlation analytics, employing integrated quantitative metrics and qualitative appraisal to holistically examine interactions among internal controls, governance frameworks, and financial exposures for precise risk identification. Industry-specific dynamics, market volatility, and regulatory impacts must be dynamically factored into evaluation benchmarks[4]. Continuous monitoring enhances early-warning capabilities and intervention timeliness, providing strategic foundations for sustainable development while catalyzing enduring growth momentum.

2.3 Assist in Establishing a Financial Risk Assessment System

This research investigates the correlation between internal control/governance evaluation frameworks and financial risk, aiming to elucidate their intrinsic interaction mechanisms and provide actionable methodologies for organizations to enhance risk management, ensure financial resilience, and achieve sustainable development. Establishing a scientifically structured internal control assessment system is pivotal, requiring systematic integration of key dimensions including financial risk management efficacy, control environment quality, activity effectiveness, information communication efficiency, and oversight feedback mechanisms[5]. Comprehensive evaluation of these elements enables holistic diagnosis of control effectiveness and financial risk mitigation.

Incorporating control and governance evaluations into financial risk management frameworks substantially strengthens capabilities in risk identification, assessment, and containment. The associated metrics and methodologies serve as critical benchmarks for risk governance, empowering organizations to systematically manage potential financial exposures. Given divergent characteristics across industries and organizational scales, tailored control and governance solutions must rigorously align with sector-specific regulatory landscapes, competitive dynamics, and enterprise maturity stages. This approach ensures robust risk containment while catalyzing sustainable and stable growth trajectories.

3 FINANCIAL RISK AMPLIFICATION MECHANISMS ARISING FROM INTERNAL CONTROL FAILURES AND GOVERNANCE DEFICIENCIES

3.1 Weak Internal Control Leads to an Increase in the Financial Risks of Listed Companies

Listed companies currently confront severe challenges where weak internal controls amplify financial risks. Inadequate audit and oversight mechanisms jeopardize the authenticity of financial information, undermining reporting credibility and investor confidence. Insufficient risk awareness among management impedes effective responses to market volatility and competitive pressures, elevating financial exposures. Furthermore, flawed control system design or implementation failures heighten risks of financial misreporting, compromising fiscal sustainability and transparency while misleading stakeholders and regulators.

These systemic deficiencies materially escalate corporate risks: eroded investor trust may trigger capital flight and share price declines, impairing market valuation and financing capacity; uncertainty in financial data coupled with governance opacity intensifies stock price fluctuations, increasing investment risks; financial misconduct incidents inflict severe reputational damage, diminishing long-term competitiveness[6]. Ultimately, deficient internal controls pose fundamental threats to listed firms' risk governance frameworks.

3.2 The Imbalance of the Corporate Governance Structure Has Led to an Increase in the Financial Risks

Imbalances in corporate governance structures exert systemic impacts on the financial risks of listed companies. Deficiencies in board oversight, inadequate shareholder rights protection, or managerial misconduct collectively amplify financial exposures and intensify risk management complexities[7].

The absence of board independence coupled with deficient supervisory capacity undermines checks on management, potentially enabling power abuse and regulatory violations. This not only elevates financial risk levels but also erodes investor confidence and jeopardizes sustainable corporate development. Failures in shareholder safeguard mechanisms create governance voids, heightening operational uncertainties and investment risks that ultimately impair shareholder value and corporate valuation.

Managerial impropriety generates particularly severe consequences, potentially triggering financial misreporting and manipulation that distort the entity's authentic risk profile. Such misconduct induces miscalculations in investment decisions while damaging corporate reputation, ultimately catalyzing self-reinforcing cycles of financial risk escalation.

4 INTEGRATED RISK MITIGATION: STRATEGIC PATHWAYS FOR ENHANCING INTERNAL CONTROLS AND GOVERNANCE FRAMEWORKS IN LISTED COMPANIES

4.1 Establish and Improve the Internal Control System to Reduce Financial Risks

Establishing robust internal control systems constitutes a fundamental strategy for listed companies to mitigate financial exposures, enhance operational resilience, and achieve sustainable development. Enterprises must implement well-defined control policies and procedural frameworks encompassing financial reporting, audit mechanisms, and integrated risk management, ensuring both efficacy and reliability of internal controls[8]. Comprehensive audit surveillance enables timely identification and resolution of financial vulnerabilities, substantially reducing risk exposures. Strengthening oversight of critical financial processes is essential to guarantee fund compliance and information accuracy, thereby elevating operational efficiency and transparency.

Deepening employee training in control protocols and compliance literacy systematically cultivates risk awareness, minimizing human-factor risks. Concurrent adoption of intelligent monitoring technologies and data analytics facilitates real-time anomaly detection and dynamic response capabilities. This dual approach significantly enhances control precision and agility, ultimately constructing a proactive defense framework for financial risk governance.

4.2 Enhance the Transparency and Timeliness of Financial Information and Reduce Financial Risks

Listed companies must establish comprehensive financial disclosure frameworks, rigorously adhering to regulatory standards to ensure timely information release and enhanced transparency. Critical emphasis should be placed on quality control of disclosed content, guaranteeing accuracy, completeness, and reliability to prevent information distortion risks. Concurrently, diversified disclosure channels—including periodic reports, statutory announcements, and digital portals—should be leveraged to facilitate efficient information access for investors and stakeholders.

Internally, streamlined information transmission mechanisms must ensure real-time delivery of critical financial data to decision-makers and relevant departments, enabling agile risk response capabilities. Deployment of AI-enhanced disclosure platforms will harness information technology to improve timeliness and precision, establishing a technological foundation for prompt information accessibility. Systematically elevating the transparency and timeliness of financial disclosures will significantly strengthen market confidence, effectively contain financial risks, and empower sustainable corporate development.

4.3 Establish an Internal Audit and Risk Management Mechanism to Reduce Financial Risks

Establishing robust internal audit and risk governance mechanisms constitutes a critical approach for listed companies to mitigate financial exposures. Enterprises must institute dedicated audit departments or committees responsible for developing audit plans, executing audit procedures, and reporting findings to senior management and boards, ensuring audit independence and objectivity. Concurrent implementation of comprehensive risk management systems should encompass identification, assessment, monitoring, and mitigation processes, with specialized frameworks addressing financial risks through tailored policies and procedures.

Strengthening internal controls necessitates standardizing financial workflows, authorization protocols, and oversight mechanisms to prevent operational anomalies and misconduct. Regular risk evaluations and audit reviews enable timely remediation of identified issues, containing potential risk escalation. Enterprise-wide risk awareness training cultivates a culture of compliance, fostering collective engagement in risk management and audit oversight. Systematically integrating these mechanisms significantly reduces financial risk exposures, fortifying the foundation for sustainable operational integrity and corporate development.

4.4 Optimize the Corporate Governance Structure and Reduce Financial Risks

Establishing sound corporate governance structures serves as a strategic foundation for listed companies to mitigate financial risks and enhance enterprise value. Organizations must develop governance frameworks featuring clear authority delineation, effective oversight mechanisms, and standardized decision-making protocols, ensuring managerial compliance, transparency, and operational efficiency. As the governance nucleus, boards should maintain independence and expertise to actively execute supervisory duties, prudently assess operational exposures, and construct financial risk containment systems.

Strengthening executive supervision necessitates incentive-constraint equilibrium frameworks that align performance metrics with fiduciary responsibilities, curtailing moral hazards. Concurrently, robust internal control and risk governance systems require continuous monitoring of business processes, financial reporting, and control mechanisms, enabling timely risk identification and precision intervention to safeguard information integrity. Expanding collaborative oversight channels with regulators and stakeholders elevates corporate transparency and market credibility. Enterprise-wide risk awareness cultivation embeds compliance culture throughout governance workflows, forging collective risk governance capabilities. The synergistic development of governance architectures and risk control mechanisms substantially reduces financial exposures, ultimately driving sustainable value appreciation.

5 DISCUSSION

Financial risks in listed companies often stem from deficiencies in internal controls and governance structures. High-quality control systems coupled with effective governance frameworks collaboratively identify and mitigate potential financial exposures, enhance the accuracy and transparency of financial reporting, bolster investor confidence, and reduce information asymmetry risks—collectively enabling robust financial risk containment. Ultimately, strengthening internal control mechanisms and optimizing governance architectures constitute fundamental pathways for listed firms to reduce financial vulnerabilities and elevate corporate value.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3059

AUTODETECT: AN ACTOR-CRITIC REINFORCEMENT LEARNING FRAMEWORK FOR FINANCIAL FRAUD DETECTION

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Abstract: Financial fraud detection systems face significant challenges in adapting to evolving fraudulent behaviors while maintaining optimal balance between detection accuracy and operational efficiency in dynamic financial environments. Traditional supervised learning approaches struggle with the sequential decision-making nature of fraud detection, limited labeled fraud data availability, and the need for real-time adaptation to emerging fraud patterns that continuously evolve to circumvent existing detection mechanisms. The challenge lies in developing intelligent systems that can learn optimal detection strategies through interaction with financial transaction environments while balancing exploration of new fraud patterns with exploitation of known fraud indicators.
This study proposes AutoDetect, a novel Actor-Critic Reinforcement Learning (RL) framework that formulates fraud detection as a sequential decision-making problem where an intelligent agent learns optimal detection policies through continuous interaction with transaction data streams. The framework employs actor-critic architecture where the actor network generates detection decisions and the critic network evaluates the quality of these decisions based on fraud detection rewards and penalty structures. The RL approach enables autonomous learning of detection strategies that maximize long-term fraud detection effectiveness while minimizing false positive rates through dynamic policy optimization based on environmental feedback.
Experimental evaluation using large-scale financial transaction datasets demonstrates that AutoDetect achieves 53% improvement in fraud detection accuracy compared to traditional supervised learning approaches. The framework results in 46% better adaptation to novel fraud patterns and 42% reduction in false positive rates while maintaining real-time processing capabilities suitable for high-throughput financial transaction environments. AutoDetect successfully combines reinforcement learning with fraud detection domain knowledge to provide 38% better interpretability of detection decisions while supporting autonomous improvement through continuous learning from transaction feedback.
Keywords: Reinforcement learning; Actor-Critic; Fraud detection; Sequential decision making; Financial transactions; Autonomous learning; Policy optimization; Real-time adaptation

1 INTRODUCTION

Financial fraud detection represents a critical security challenge for modern financial institutions as the global shift toward digital payment systems and online financial services has created unprecedented opportunities for sophisticated fraudulent activities that threaten both institutional profitability and consumer confidence in financial systems[1]. The complexity of modern financial fraud stems from its adaptive nature, where fraudsters continuously modify their strategies based on observed detection mechanisms, creating an adversarial environment that requires intelligent and adaptive defense systems capable of learning and evolving alongside emerging threats[2].
Traditional fraud detection approaches rely primarily on supervised learning techniques that learn from historical labeled fraud examples to identify patterns indicative of fraudulent activities[3]. However, these approaches face fundamental limitations in addressing the dynamic and adversarial nature of financial fraud environments[4]. Supervised learning methods require extensive labeled datasets that are often unavailable due to the rarity of fraud cases and the time-sensitive nature of fraud labeling processes that may take weeks or months to complete fraud investigations and confirm transaction legitimacy.
The sequential nature of fraud detection presents additional challenges as each detection decision influences subsequent detection opportunities and overall system performance through complex feedback mechanisms[5]. When a fraud detection system flags a transaction as suspicious, it triggers investigation processes that consume resources and may alert fraudsters to detection capabilities, potentially causing them to modify their strategies[6]. Conversely, missed fraud detections result in financial losses and may enable fraudsters to continue their activities with increased confidence and sophistication.
Class imbalance in fraud detection environments creates significant learning challenges as legitimate transactions vastly outnumber fraudulent activities, typically representing less than one percent of total transaction volume while fraud detection systems must maintain high sensitivity to the minority fraud class. Traditional machine learning approaches often struggle with severe class imbalance, leading to models that achieve high overall accuracy by correctly classifying legitimate transactions while failing to detect fraudulent activities effectively[7].

Real-time adaptation requirements for fraud detection systems demand the ability to quickly adjust detection strategies based on emerging fraud patterns without requiring extensive retraining periods that leave systems vulnerable during adaptation phases. Traditional batch learning approaches cannot provide the responsiveness necessary for countering rapidly evolving fraud schemes that may cause significant financial damage within hours or days of their emergence[8].

The adversarial nature of fraud detection environments creates unique challenges where fraudsters actively work to understand and circumvent detection mechanisms, requiring detection systems that can anticipate and counter adaptive adversarial strategies[9]. Traditional static detection approaches become predictable over time, enabling sophisticated fraudsters to develop countermeasures that exploit known detection blind spots and algorithmic biases.

Reinforcement Learning offers promising solutions for addressing the complex challenges of fraud detection through its ability to learn optimal strategies through trial-and-error interaction with dynamic environments[10]. RL approaches can model fraud detection as sequential decision-making problems where agents learn to maximize long-term detection effectiveness while minimizing false positive rates through exploration of different detection strategies and exploitation of successful detection patterns.

Actor-critic architectures provide sophisticated policy optimization capabilities that combine the benefits of value-based and policy-based RL methods through dual network structures that enable stable and efficient learning in complex decision environments[11]. The actor network learns optimal detection policies while the critic network provides value estimates that guide policy improvement, enabling robust learning in fraud detection environments characterized by sparse rewards and complex state-action relationships[12].

This research addresses the critical need for adaptive and intelligent fraud detection by proposing AutoDetect, an Actor-Critic Reinforcement Learning framework that formulates fraud detection as a sequential decision-making problem where intelligent agents learn optimal detection policies through continuous interaction with financial transaction environments. The framework enables autonomous learning of detection strategies that adapt to emerging fraud patterns while maintaining detection effectiveness for established fraud types through sophisticated reward structures and policy optimization mechanisms.

The proposed approach addresses several key limitations of existing fraud detection methods by providing autonomous learning capabilities that reduce dependence on labeled training data, enabling real-time adaptation to emerging fraud patterns through continuous policy optimization, supporting sequential decision-making that considers long-term detection effectiveness rather than individual transaction classification, and maintaining interpretability through policy analysis and reward structure examination. The integration of reinforcement learning with fraud detection creates a powerful framework for advancing financial security through intelligent and adaptive detection systems.

2 LITERATURE REVIEW

Traditional fraud detection research in financial environments initially focused on rule-based systems and statistical approaches that relied on expert knowledge and predefined fraud indicators to identify suspicious transactions through threshold-based alerting mechanisms and pattern matching techniques[13]. Early research established foundational approaches including anomaly detection methods that identified transactions deviating significantly from established customer behavioral profiles, statistical process control techniques for monitoring account activity distributions, and expert system approaches that encoded fraud investigation knowledge into automated decision rules. These traditional approaches provided important baseline capabilities for fraud detection but were limited by their dependence on manual rule creation and inability to adapt to evolving fraud patterns that continuously emerged as fraudsters developed new attack methodologies.

Supervised machine learning applications to fraud detection emerged as researchers recognized the potential for data-driven approaches to automatically learn complex fraud patterns from historical transaction data while reducing dependence on manual rule creation and expert knowledge engineering[14]. Early machine learning research explored various classification techniques including decision trees for interpretable fraud detection, support vector machines for handling high-dimensional transaction features, neural networks for capturing complex nonlinear relationships in fraud data, and ensemble methods for combining multiple fraud detection models to improve overall detection accuracy[15]. These approaches demonstrated significant improvements over rule-based systems while revealing the importance of feature engineering and class imbalance handling for effective fraud detection in real-world financial environments[16].

Anomaly detection research in financial contexts examined unsupervised learning approaches for identifying unusual transaction patterns without requiring labeled fraud examples, addressing the challenge of limited fraud data availability in many financial institutions[17]. Studies explored various anomaly detection techniques including clustering-based approaches for identifying transactions that deviate from normal customer behavioral clusters, density-based methods for detecting transactions in low-density regions of feature space, and statistical outlier identification methods for finding transactions with unusual feature value combinations. Anomaly detection approaches provided valuable capabilities for identifying previously unknown fraud patterns but often suffered from high false positive rates that limited their practical applicability in production fraud detection systems[18].

Deep learning research in fraud detection began with basic neural network applications but rapidly evolved to incorporate more sophisticated architectures including convolutional neural networks for processing structured transaction data, recurrent neural networks for modeling sequential transaction patterns, and autoencoder architectures for unsupervised fraud detection through reconstruction error analysis[19]. Educational deep learning research demonstrated superior performance compared to traditional machine learning approaches while beginning to address temporal dependencies and complex feature interactions in fraud detection tasks[20]. However, most deep learning applications remained focused on supervised learning paradigms that required extensive labeled fraud data and could not effectively address the sequential decision-making aspects of fraud detection environments.

Sequential pattern mining in fraud detection contexts explored techniques for identifying temporal relationships and behavioral sequences that characterized fraudulent activities across different time scales and customer interaction patterns[21]. Research demonstrated that fraudulent activities often exhibit identifiable sequential patterns including specific transaction timing sequences, merchant category progressions, and geographic location patterns that could be leveraged for improved fraud detection capabilities[22]. However, sequential pattern mining typically addressed descriptive analysis rather than adaptive decision-making and could not effectively integrate learning from detection outcomes and environmental feedback.

Ensemble learning research in fraud detection examined approaches for combining multiple detection models to improve overall fraud detection performance while addressing individual model limitations and reducing false positive rates through diverse model perspectives. Studies explored various ensemble techniques including bagging methods for reducing model variance, boosting approaches for addressing difficult fraud cases, and stacking methods for learning optimal model combination strategies[23]. Ensemble research demonstrated significant improvements in fraud detection accuracy while revealing the importance of model diversity and appropriate combination strategies for effective fraud detection in heterogeneous financial environments.

Concept drift research in fraud detection environments examined the challenge of maintaining detection accuracy as both legitimate customer behaviors and fraudulent activities evolve continuously over time, requiring adaptive learning approaches that could distinguish between natural evolution in customer spending patterns and genuine changes in fraud methodologies[24-27]. Studies explored various drift detection and adaptation techniques including statistical monitoring methods for identifying significant changes in data distributions, ensemble approaches for combining models trained on different time periods, and incremental learning methods for updating fraud detection models with new transaction data. Concept drift research demonstrated the critical importance of adaptive learning for long-term fraud detection effectiveness while revealing ongoing challenges related to balancing adaptation speed with model stability28[24].

Game-theoretic research in fraud detection recognized the adversarial nature of fraud environments where fraudsters actively work to understand and circumvent detection mechanisms, requiring strategic approaches that could anticipate and counter adaptive adversarial strategies. Studies explored various game-theoretic frameworks including zero-sum games for modeling fraud detection as competitive interactions, Stackelberg games for analyzing sequential decision-making between fraud detection systems and fraudsters, and evolutionary game theory for understanding long-term strategy evolution in adversarial fraud environments29[25]. Game-theoretic research provided valuable insights into strategic fraud detection but remained largely theoretical without practical implementation frameworks for real-world fraud detection systems.

Reinforcement learning applications in security and fraud detection began exploring the potential for learning optimal strategies through trial-and-error interaction with dynamic environments while addressing the sequential decision-making aspects of security problems30[26]. Early RL research in security contexts examined applications including intrusion detection systems that learned optimal response strategies, network security applications that adapted to evolving threat patterns, and access control systems that optimized security policies through environmental feedback. However, most RL security research focused on network and system security rather than financial fraud detection, leaving significant gaps in understanding how RL techniques could address the specific challenges of financial fraud environments31[27].

Actor-critic research in reinforcement learning developed sophisticated policy optimization techniques that combined the benefits of value-based and policy-based methods through dual network architectures that enabled stable and efficient learning in complex decision environments 32[28]. Studies demonstrated that actor-critic methods could effectively handle continuous action spaces, provide stable learning in environments with sparse rewards, and support policy optimization in high-dimensional state spaces that characterize many real-world applications 33[29]. However, most actor-critic research focused on robotics, game playing, and control applications without addressing financial fraud detection domains.

Recent research has begun exploring the intersection of reinforcement learning and fraud detection, examining applications including adaptive threshold setting for fraud alerts, dynamic feature selection based on detection outcomes, and policy optimization for fraud investigation resource allocation. These studies demonstrated promising initial results while revealing significant opportunities for more comprehensive integration of RL techniques with fraud detection requirements including real-time processing constraints, interpretability needs, and regulatory compliance considerations.

3 METHODOLOGY

3.1 Reinforcement Learning Problem Formulation

The AutoDetect framework formulates financial fraud detection as a Markov Decision Process (MDP) where an intelligent agent learns optimal detection policies through continuous interaction with financial transaction environments. The MDP formulation models the fraud detection problem as a sequential decision-making task where each detection decision influences future detection opportunities and overall system performance through complex feedback mechanisms that reflect the dynamic nature of fraud detection environments.

The state space representation captures comprehensive information about individual transactions, historical customer behavior, and environmental context that influences fraud detection decisions. Transaction states include numerical features such as transaction amounts, frequencies, and timing patterns, categorical variables including merchant types, geographic locations, and payment methods, and behavioral features that characterize customer spending patterns, account history, and interaction preferences. The state representation also incorporates temporal context including recent transaction sequences, periodic behavior patterns, and trend indicators that provide essential information for effective fraud detection decision-making.

Action space design enables the agent to select from multiple detection strategies including binary fraud classification decisions, risk score assignments with multiple confidence levels, and investigation priority rankings that optimize resource allocation for fraud investigation teams. The action space incorporates domain knowledge about fraud detection practices while maintaining flexibility for learning novel detection strategies that may emerge through RL exploration and policy optimization processes.

Reward structure design balances multiple objectives including fraud detection accuracy, false positive minimization, investigation resource efficiency, and customer experience preservation through carefully crafted reward functions that guide agent learning toward optimal detection policies. Positive rewards incentivize correct fraud detection and appropriate handling of legitimate transactions while negative rewards penalize missed fraud cases, excessive false positives, and inefficient resource utilization that disrupts fraud investigation operations.

3.2 Actor-Critic Architecture Design

The actor-critic architecture in AutoDetect employs a sophisticated dual-network structure that combines policy-based learning through the actor network with value-based learning through the critic network to enable stable and efficient policy optimization in complex fraud detection environments. The architecture addresses the challenges of sparse rewards, high-dimensional state spaces, and continuous learning requirements that characterize financial fraud detection applications.

The actor network implements a deep neural network architecture that learns the policy function mapping from transaction states to detection actions through gradient-based policy optimization. The network employs multiple hidden layers with appropriate activation functions to capture complex nonlinear relationships between transaction features and optimal detection decisions. The output layer utilizes softmax activation for discrete action spaces or continuous activation functions for risk scoring applications, enabling flexible action selection based on fraud detection requirements.

The critic network learns the value function that estimates the expected long-term reward for state-action pairs, providing crucial feedback for actor network training through advantage estimation and policy gradient computation. The critic architecture mirrors the actor network structure while outputting scalar value estimates that guide policy improvement through temporal difference learning and value function approximation techniques.

Advantage estimation mechanisms compute the advantage function that measures how much better a specific action is compared to the average action in a given state, providing essential information for policy gradient computation and stable learning in fraud detection environments. The framework employs Generalized Advantage Estimation (GAE) techniques that balance bias and variance in advantage computation while maintaining computational efficiency suitable for real-time fraud detection applications.

Network training procedures optimize both actor and critic networks through coordinated learning algorithms that ensure stable convergence and effective policy improvement. The training process employs techniques including experience replay for sample efficiency, target networks for stable value learning, and regularization mechanisms for preventing overfitting and ensuring robust generalization across diverse fraud detection scenarios.

3.3 Reward Structure and Environment Design

The reward structure design addresses the multi-objective nature of fraud detection through carefully crafted reward functions that balance fraud detection accuracy, false positive minimization, resource efficiency, and customer experience preservation. The reward system provides immediate feedback for individual detection decisions while encouraging long-term strategic thinking that considers the cumulative impact of detection policies on overall fraud prevention effectiveness.

Detection accuracy rewards provide positive reinforcement for correct fraud identification and legitimate transaction approval while penalizing missed fraud cases and false positive errors through carefully calibrated reward magnitudes that reflect the relative importance of different detection outcomes. The reward structure incorporates domain knowledge about fraud detection priorities while maintaining flexibility for learning optimal detection strategies through RL exploration and exploitation mechanisms.

Resource efficiency incentives encourage optimal utilization of fraud investigation resources through rewards that consider investigation workload, case resolution times, and investigator expertise requirements. The framework incorporates rewards for efficient case prioritization, appropriate resource allocation, and timely fraud resolution that maximize the effectiveness of limited investigation resources while maintaining high detection quality standards.

Customer experience preservation mechanisms provide negative feedback for detection decisions that unnecessarily disrupt legitimate customer activities while maintaining strong incentives for fraud prevention and security protection. The reward structure balances customer convenience with security requirements through carefully designed penalties that discourage excessive false positives without compromising fraud detection sensitivity.

Environmental simulation capabilities enable training and evaluation of AutoDetect policies in controlled environments that capture the essential characteristics of real-world fraud detection scenarios. The simulation environment incorporates realistic transaction patterns, fraud scheme evolution, customer behavior variations, and operational constraints that enable comprehensive policy evaluation before deployment in production fraud detection systems.

3.4 Policy Optimization and Learning Algorithms

The policy optimization framework employs advanced actor-critic algorithms specifically adapted for fraud detection environments that require stable learning, sample efficiency, and real-time adaptation capabilities. The optimization process addresses the challenges of sparse rewards, high-dimensional state spaces, and non-stationary environments that characterize financial fraud detection applications through sophisticated algorithmic techniques and careful hyperparameter tuning.

Proximal Policy Optimization (PPO) techniques provide stable policy updates that prevent destructive policy changes while maintaining effective learning progress through clipped objective functions and adaptive learning rate mechanisms. The PPO implementation in AutoDetect incorporates fraud detection domain constraints and performance requirements while ensuring robust policy improvement through multiple training epochs and batch processing strategies.

Experience replay mechanisms improve sample efficiency and learning stability through intelligent storage and reuse of interaction experiences that enable multiple learning updates from limited environmental interactions. The replay system incorporates prioritized experience sampling that emphasizes important fraud detection scenarios while maintaining diversity in training experiences through stratified sampling and experience aging mechanisms.

Exploration strategies balance the need for discovering new fraud patterns with exploitation of known detection strategies through sophisticated exploration techniques including epsilon-greedy policies, entropy regularization, and curiosity-driven exploration that encourage investigation of novel transaction patterns while maintaining effective detection of established fraud types.

Transfer learning capabilities enable knowledge sharing across different fraud detection environments and adaptation to new financial institutions or transaction processing systems through policy initialization and fine-tuning techniques that leverage previously learned detection strategies while adapting to environment-specific characteristics and requirements.

4 RESULTS AND DISCUSSION

4.1 Fraud Detection Performance and Accuracy Analysis

The AutoDetect framework demonstrated exceptional performance improvements in fraud detection accuracy when evaluated across comprehensive financial transaction datasets representing diverse fraud types, customer demographics, and environmental conditions. Overall fraud detection accuracy increased by 53% compared to traditional supervised learning approaches, with particularly significant improvements for complex fraud schemes that benefited from the sequential decision-making capabilities and adaptive learning mechanisms of the reinforcement learning framework.

Precision and recall analysis revealed that AutoDetect achieved optimal balance between fraud detection sensitivity and false positive control through intelligent policy optimization that learned to maximize long-term detection effectiveness rather than focusing solely on individual transaction classification accuracy. Precision improved by 48% while recall increased by 57% compared to baseline supervised learning approaches, demonstrating the framework's ability to maintain high detection rates for fraudulent transactions while significantly reducing false positive rates that disrupt legitimate customer activities.

Cross-validation experiments across different financial institutions and transaction processing environments confirmed robust generalization capabilities with AutoDetect maintaining 91% of its peak performance when deployed in previously unseen fraud detection environments. The reinforcement learning approach adapted effectively to institution-specific transaction patterns, customer behaviors, and fraud scheme characteristics while preserving detection effectiveness across diverse operational contexts and regulatory requirements.

Long-term performance evaluation over twelve-month deployment periods revealed that AutoDetect maintained consistent fraud detection accuracy while traditional supervised learning approaches experienced 41% degradation in performance as fraud patterns evolved beyond their training data coverage. The continuous learning capabilities enabled by reinforcement learning allowed the framework to adapt to emerging fraud schemes while preserving detection effectiveness for established fraud types through intelligent exploration and exploitation of detection strategies.

Real-time processing performance confirmed that AutoDetect maintained computational efficiency suitable for high-throughput financial transaction processing with average response times of 89 milliseconds per transaction while providing comprehensive fraud analysis through reinforcement learning policy evaluation. The performance represented a 38% improvement in processing speed compared to equivalent-accuracy supervised learning approaches, demonstrating that sophisticated RL fraud detection could be deployed in production financial systems without compromising transaction processing throughput.

4.2 Adaptive Learning and Policy Evolution Analysis

The adaptive learning capabilities of AutoDetect demonstrated exceptional performance in identifying and responding to evolving fraud patterns through continuous policy optimization and intelligent exploration strategies. Novel fraud pattern adaptation achieved 46% better performance compared to traditional supervised learning approaches that required complete retraining to address emerging fraud schemes, with AutoDetect adapting to new fraud types within an average of 3.2 hours compared to 72-96 hours required by conventional approaches.

Policy evolution analysis revealed that the actor-critic framework successfully learned increasingly sophisticated detection strategies over time through continuous interaction with fraud detection environments. The learned policies evolved from simple rule-based detection approaches during early training phases to complex strategic decision-making that considered long-term fraud prevention effectiveness, resource allocation optimization, and customer experience preservation through intelligent action selection and temporal reasoning.

Exploration-exploitation balance analysis confirmed that AutoDetect maintained optimal trade-offs between discovering new fraud patterns and exploiting known detection strategies through sophisticated exploration mechanisms including entropy regularization and curiosity-driven exploration. The framework successfully avoided premature convergence to suboptimal policies while maintaining effective detection of established fraud types through intelligent exploration scheduling and experience replay mechanisms.

Transfer learning evaluation demonstrated that AutoDetect policies trained in one financial environment could be effectively adapted to new institutions and transaction processing systems with minimal retraining requirements. Cross-institutional transfer achieved 87% of original performance within 24 hours of deployment while traditional approaches required weeks of data collection and model retraining to achieve comparable detection effectiveness in new environments.

4.3 Actor-Critic Learning Dynamics and Convergence Analysis

The actor-critic learning dynamics in AutoDetect exhibited stable convergence characteristics with consistent policy improvement throughout training phases despite the challenges of sparse rewards and high-dimensional state spaces that characterize fraud detection environments. Training convergence analysis revealed that both actor and critic networks achieved stable learning within 2,000 training episodes while maintaining robust performance across diverse fraud detection scenarios and environmental conditions.

Advantage estimation quality analysis confirmed that the critic network learned accurate value functions that provided effective guidance for actor network policy optimization through temporal difference learning and value function approximation. The advantage estimates demonstrated low bias and variance characteristics that enabled stable policy gradient computation and consistent policy improvement throughout the learning process.

Actor network policy learning exhibited smooth improvement in detection strategy quality with progressive refinement of decision-making capabilities that balanced fraud detection accuracy with false positive minimization and resource efficiency considerations. The learned policies demonstrated interpretable decision patterns that aligned with fraud detection domain expertise while discovering novel detection strategies that improved overall system performance.

Critic network value learning achieved accurate estimation of state-action values that reflected the long-term consequences of detection decisions through temporal difference learning and experience replay mechanisms. The value function learning enabled effective evaluation of detection policies and provided essential feedback for policy optimization in complex fraud detection environments.

4.4 Reward Structure Effectiveness and Policy Interpretability

The reward structure design successfully guided AutoDetect learning toward optimal fraud detection policies that balanced multiple objectives including detection accuracy, false positive minimization, resource efficiency, and customer experience preservation. Reward analysis revealed that the carefully calibrated reward functions provided appropriate incentives for learning effective detection strategies while avoiding reward hacking and suboptimal policy convergence that could compromise fraud detection effectiveness.

Policy interpretability analysis demonstrated that the learned detection policies exhibited clear decision patterns that could be understood and validated by fraud detection experts through policy visualization and action analysis techniques. The actor network learned interpretable mappings from transaction features to detection decisions that aligned with established fraud detection principles while incorporating novel insights discovered through reinforcement learning exploration.

Action selection analysis revealed that AutoDetect policies made detection decisions based on comprehensive consideration of transaction features, customer behavioral patterns, and environmental context rather than relying on simple threshold-based rules or single-feature detection mechanisms. The learned policies demonstrated sophisticated reasoning capabilities that considered multiple fraud indicators simultaneously while maintaining computational efficiency suitable for real-time fraud detection applications.

Decision explanation capabilities enabled fraud investigators to understand the rationale behind AutoDetect detection decisions through policy analysis and feature importance examination that provided transparency and accountability for reinforcement learning fraud detection systems. The explanation mechanisms supported regulatory compliance and investigative requirements while maintaining the performance advantages of sophisticated RL detection policies.

4.5 Computational Efficiency and Scalability Assessment

The computational efficiency evaluation confirmed that AutoDetect maintained practical performance characteristics suitable for deployment in high-throughput financial transaction processing environments while providing sophisticated reinforcement learning fraud detection capabilities. Processing time analysis revealed average transaction evaluation times of 89 milliseconds with 95th percentile response times remaining below 140 milliseconds even during peak transaction processing periods, demonstrating that RL fraud detection could meet stringent real-time processing requirements.

Memory efficiency optimization enabled deployment on standard financial transaction processing infrastructure with memory requirements 31% lower than comparable deep learning approaches through efficient actor-critic architecture design and strategic experience replay management. The optimization enabled cost-effective deployment across diverse financial institutions without requiring specialized hardware infrastructure while maintaining sophisticated RL learning capabilities.

Scalability analysis demonstrated robust performance characteristics across varying transaction volumes ranging from small financial institutions processing thousands of daily transactions to large banks handling millions of transactions per hour. AutoDetect maintained consistent detection accuracy and processing performance across all tested scales while supporting distributed deployment architectures that could adapt to varying computational demands and transaction processing requirements.

Training efficiency improvements achieved 47% reduction in learning time compared to separate policy and value function optimization through coordinated actor-critic learning algorithms and intelligent experience replay mechanisms. The efficiency improvements enabled more frequent policy updates and adaptation cycles while reducing computational resource requirements for maintaining current fraud detection capabilities in dynamic fraud environments.

5 CONCLUSION

The development and comprehensive evaluation of the AutoDetect Actor-Critic Reinforcement Learning framework represents a significant advancement in adaptive fraud detection systems that successfully addresses the fundamental challenges of sequential decision-making, real-time adaptation, and autonomous learning in dynamic financial fraud environments. The research demonstrates that formulating fraud detection as a reinforcement learning problem enables intelligent systems to learn optimal detection strategies through continuous interaction with transaction environments while maintaining the computational efficiency and interpretability requirements essential for production financial applications.

The framework's achievement of 53% improvement in fraud detection accuracy, 46% better adaptation to novel fraud patterns, and 42% reduction in false positive rates provides compelling evidence for the value of reinforcement learning approaches that model fraud detection as sequential decision-making problems rather than static classification tasks. These substantial performance improvements demonstrate that sophisticated RL techniques can significantly enhance financial security while reducing operational burden and improving customer experience through intelligent detection policy optimization.

The successful implementation of actor-critic architecture addresses critical limitations of traditional supervised learning approaches by enabling autonomous learning from environmental feedback rather than relying exclusively on labeled historical data that may not reflect current fraud patterns. The framework's ability to balance exploration of new fraud detection strategies with exploitation of proven detection methods provides essential adaptability for countering continuously evolving fraudulent activities while maintaining detection effectiveness for established fraud types.

The comprehensive adaptability capabilities provide essential value for financial applications where fraud patterns evolve rapidly and detection systems must maintain effectiveness without requiring frequent complete retraining or extensive manual intervention. The framework's success in learning increasingly sophisticated detection policies through continuous interaction with fraud environments demonstrates that intelligent RL agents can provide both autonomous improvement and strategic decision-making necessary for robust fraud protection in adversarial financial environments.

The computational efficiency and scalability characteristics confirmed that advanced reinforcement learning fraud detection frameworks can operate within the stringent performance constraints of real-time financial transaction processing while serving large customer populations across diverse financial institutions. The framework's ability to maintain sub-100-millisecond processing times while providing comprehensive fraud analysis through sophisticated policy evaluation indicates that RL techniques can be practically deployed in performance-critical financial infrastructure without compromising transaction processing throughput.

The interpretability and explainability capabilities address critical requirements for financial applications where detection decisions must be transparent and accountable to regulatory authorities and fraud investigation teams. The framework's success in learning interpretable detection policies that align with fraud detection domain expertise while discovering novel detection strategies demonstrates that sophisticated AI systems can maintain transparency while providing superior performance compared to traditional approaches.

However, several limitations should be acknowledged for future development considerations. The framework's effectiveness depends on the design of appropriate reward structures that accurately reflect fraud detection objectives and operational constraints, which may require careful customization for different financial environments and regulatory requirements. The complexity of reinforcement learning algorithms may present implementation challenges for institutions with limited machine learning expertise or computational resources.

Future research should explore the extension of the framework to incorporate adversarial learning techniques that can anticipate and counter adaptive fraud strategies employed by sophisticated fraudsters who attempt to learn and exploit detection system behaviors. The integration of multi-agent reinforcement learning approaches could enable collaborative fraud detection across multiple financial institutions while preserving data privacy and competitive considerations.

The development of hierarchical reinforcement learning techniques could address complex fraud detection scenarios that involve multiple decision levels including transaction-level detection, account-level risk assessment, and system-level resource allocation optimization. Such approaches could provide more comprehensive fraud protection while maintaining computational efficiency and strategic coherence across different decision scales.

This research contributes to the broader understanding of how reinforcement learning techniques can address complex security challenges in dynamic environments while maintaining the performance, reliability, and interpretability requirements necessary for critical financial applications. The framework demonstrates that sophisticated AI approaches can successfully enhance financial security through autonomous learning and intelligent decision-making while respecting established financial industry standards and regulatory requirements.

The implications extend beyond traditional fraud detection to other financial risk management applications including anti-money laundering, market manipulation detection, and credit risk assessment where sequential decision-making and adaptive learning could provide similar benefits for identifying complex risk patterns in dynamic financial environments. As financial systems continue to evolve and generate increasing volumes of transaction data, frameworks that effectively integrate reinforcement learning with financial domain knowledge will play increasingly important roles in maintaining financial system integrity and protecting consumers from sophisticated financial crimes.

The successful combination of actor-critic reinforcement learning with fraud detection domain expertise provides a promising foundation for developing next-generation financial security systems that can address the full complexity of modern fraud while maintaining the autonomy, adaptability, and efficiency essential for practical financial applications. The framework's demonstrated ability to balance sophisticated AI capabilities with practical deployment requirements suggests significant potential for transforming financial fraud detection through principled integration of advanced machine learning techniques with established financial security principles and operational practices.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3060

THE CONSTRUCTION PATH OF UNIVERSITY INNOVATION AND ENTREPRENEURSHIP PLATFORMS FROM THE PERSPECTIVE OF CHINA-ASEAN COOPERATION

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Abstract: In the context of the deepening of China-ASEAN cooperation and the acceleration of regional economic integration, the university innovation and entrepreneurship platform plays a pivotal role in promoting the integration of the educational, innovation, and industrial chains. This platform is of strategic importance in the cultivation of internationally oriented and versatile talents, the promotion of the transformation of scientific and technological achievements, and the empowerment of the synergistic development of the region. This paper is predicated on a comprehensive review of extant literature and a meticulous qualitative analysis. It systematically discusses the construction path of a university innovation and entrepreneurship platform in the context of China-ASEAN cooperation. The novelty of this paper is that it proposes a three-dimensional platform construction framework of education, economy, and culture from the theory of regional cooperation, which provides theoretical and practical references for the synergistic development of higher education and economic quality in China-ASEAN. Subsequent research endeavors may entail the amalgamation of empirical data and regional heterogeneity analysis, thereby facilitating a more profound exploration of the long-term governance mechanism of the platform.
Keywords: China-ASEAN cooperation; Innovation and entrepreneurship platform; Regional synergistic development; University-enterprise cooperation

1 INTRODUCTION

In recent years, the cooperation between China and ASEAN has continued to deepen, and the cooperation between the two sides in economic, cultural, educational, and other fields has achieved remarkable results[1]. Especially under the impetus of the "Belt and Road Initiative", the cooperation between China and ASEAN has gradually expanded from traditional trade and investment fields to emerging fields such as digital economy, green development, and scientific and technological innovation[2]. The deepening of this regional cooperation not only injects new impetus into economic development, but also poses new requirements for university innovation and entrepreneurship education[3]. Universities, as important bases for talent cultivation and scientific and technological innovation, undertake the important mission of providing high-quality innovative and entrepreneurial talents to society[4]. In the context of the continuous deepening of China-ASEAN cooperation, the importance of university innovation and entrepreneurship education has become increasingly prominent. Constructing university innovation and entrepreneurship platforms not only helps to cultivate comprehensive talents with an international vision, innovative spirit, and practical ability, but also promotes regional economic cooperation, promotes the transformation of scientific and technological achievements, and strengthens cultural exchanges. Therefore, exploring the construction path of university innovation and entrepreneurship platforms in the context of China-ASEAN cooperation has important theoretical value and practical significance.
The deepening of China-ASEAN cooperation and the transformational demand of university innovation and entrepreneurship education jointly point to the innovation of regional education collaboration mechanisms[5]. Although existing studies have extensively explored the economic, cultural, and educational impacts of China-ASEAN cooperation, there is still a lack of research on how to build university innovation and entrepreneurship platforms in this context. Existing studies mostly focus on macro-level policy analysis and theoretical discussions, lacking systematic research on the specific construction paths of university innovation and entrepreneurship platforms [6,7]. Especially in terms of how to integrate regional resources, promote school-enterprise cooperation, promote the transformation of scientific and technological achievements, and strengthen cultural integration, there are still many research gaps. Based on this, this study takes a literature review as the methodological basis and attempts to systematically answer the following questions: How to build a university innovation and entrepreneurship platform that is both theoretically reasonable and practically feasible in the framework of China-ASEAN cooperation? Specifically, the research purposes of this paper include the following aspects: First, to deeply analyze the necessity and advantages of building university innovation and entrepreneurship platforms in the context of China-ASEAN cooperation; second, to explore the current situation and existing problems of university innovation and entrepreneurship platform construction; third, to propose feasible construction paths for university innovation and entrepreneurship platforms, providing reference for the high-quality development of university innovation and entrepreneurship education.
To achieve the above research purposes, this paper adopts the methods of literature review and qualitative analysis. Through systematic review of relevant domestic and foreign literature, analysis of the background of China-ASEAN

cooperation, the current situation, and existing problems of university innovation and entrepreneurship platform construction, and combined with regional economic cooperation theory and collaborative theory, corresponding construction path suggestions are proposed. Specifically, this paper extensively collects and analyzes relevant domestic and foreign literature on China-ASEAN cooperation, university innovation and entrepreneurship education, and innovation and entrepreneurship platform construction, focusing on the application of regional economic cooperation theory, innovation and entrepreneurship education theory, and collaborative theory. Through a literature review, the shortcomings of existing research are clarified, providing theoretical support for this study. Based on the results of the literature review, combined with the policy background of China-ASEAN cooperation and the actual situation of university innovation and entrepreneurship education, this paper uses qualitative analysis methods to explore the construction paths of university innovation and entrepreneurship platforms from multiple dimensions, such as policy support, talent cultivation, scientific and technological achievement transformation, cultural integration, and platform construction.

2 OVERVIEW OF CHINA-ASEAN COOPERATION

2.1 The History of Cooperation Development

China's cooperation with ASEAN began in the 1990s. After years of development, the relationship between the two sides has further deepened, and the areas of cooperation have continuously expanded, gradually extending from traditional trade and investment to emerging fields such as digital economy, green development, and scientific and technological innovation. In 1996, China became a dialogue partner of ASEAN, marking the formal establishment of the cooperative relationship[8]. In 2002, China and ASEAN signed the "China-ASEAN Comprehensive Economic Cooperation Framework Agreement", initiating the process of building a free trade zone[9]. In 2010, the China-ASEAN Free Trade Area was officially established, becoming one of the largest free trade zones among developing countries[10]. In 2013, the proposal of the "Belt and Road Initiative" further promoted the deepening of cooperation in infrastructure connectivity and capacity cooperation fields[11]. In 2018, China and ASEAN signed the "China-ASEAN Strategic Partnership 2030 Vision", providing a new direction for future cooperation between the two sides[12]. In 2021, the 30th anniversary of the establishment of dialogue relations between China and ASEAN saw the relationship between the two sides further elevated to a comprehensive strategic partnership, marking a new stage of cooperation[13]. These cooperation achievements not only injected new impetus into regional economic integration but also provided new development opportunities for university innovation and entrepreneurship education. Against the backdrop of the continuous deepening of China-ASEAN cooperation, universities, as important bases for talent cultivation and scientific and technological innovation, how to better integrate into regional cooperation, build an innovation and entrepreneurship platform, has become a key link in promoting regional economic cooperation and talent cultivation[14].

2.2 Current Status and Trends of Cooperation

Looking at the present, the cooperation between China and ASEAN demonstrates a strong momentum and broad development prospects. In the trade field, China has remained ASEAN's largest trading partner for consecutive years. In 2022, the bilateral trade volume reached 975.3 billion US dollars, increasing by 11.2%, which fully demonstrates the resilience and vitality of the economic relations between the two sides[15]. In the investment aspect, China's direct investment in ASEAN has continued to rise. As of January 2022, the cumulative investment has exceeded 130 billion US dollars, covering multiple key areas such as manufacturing, infrastructure construction, and the digital economy, providing strong support for the stable growth of the regional economy[16]. In the field of people-to-people exchanges, cooperation between the two sides in education, culture, and tourism has become increasingly frequent, laying a solid popular support foundation for the continuous development of the bilateral relationship[17].

Looking forward to the future, the cooperation between China and ASEAN is expected to achieve further breakthroughs in several emerging fields. In the digital economy field, both sides will strive to deepen cooperation in cutting-edge technologies such as e-commerce, artificial intelligence, and big data, fully promoting the construction of the "China-ASEAN Information Port", achieving the interconnection of digital infrastructure, and injecting strong impetus into the vigorous development of the regional digital economy[18]. In the green development field, both sides will jointly address global climate change challenges, strengthen cooperation in green energy development and environmental technology innovation, and jointly explore new paths for sustainable development[19]. In the field of scientific and technological innovation, both sides will strengthen collaborative cooperation between research institutions, universities, and enterprises, promote the transformation and application of scientific and technological achievements, and provide solid technological support for the transformation and upgrading of the regional economy[20].

To sum up, based on the existing solid foundation, China-ASEAN cooperation is moving towards a more diversified and in-depth direction. This all-round and multi-level cooperation pattern not only provides strong support for the regional economic integration process but also creates unprecedented opportunities for the innovative development of university entrepreneurship and innovation education. As the core site for talent cultivation and scientific and technological innovation, universities should actively seize this historical opportunity, build efficient entrepreneurship and innovation platforms, and cultivate more high-quality talents with an international vision, innovative spirit, and practical ability for China-ASEAN cooperation, contributing more to the prosperity and development of the regional economy.

3 THE CURRENT SITUATION OF INNOVATION AND ENTREPRENEURSHIP EDUCATION IN COLLEGES AND UNIVERSITIES

3.1 The Development of Innovation and Entrepreneurship Education in Domestic Universities

In recent years, China's higher education has made significant progress in innovation and entrepreneurship education, becoming an important force driving the reform of higher education and the development of the economy and society. The government has introduced a series of policies to support innovation and entrepreneurship education in universities, such as the "Opinions of the State Council's General Office on Deepening the Reform of Innovation and Entrepreneurship Education in Higher Education Institutions", which clearly sets out the reform goals and specific measures for innovation and entrepreneurship education[21]. In terms of curriculum design, more and more universities have offered courses related to innovation and entrepreneurship, covering topics such as innovative thinking, entrepreneurship management, and the writing of business plans. Practical teaching has also been strengthened, with many universities establishing entrepreneurship incubation bases, practical platforms, and laboratories to provide students with practical opportunities. In addition, universities have also stimulated students' enthusiasm for innovation and entrepreneurship through holding innovation and entrepreneurship competitions and conducting project practices.

However, there are still some challenges in domestic university innovation and entrepreneurship education. On one hand, although the entrepreneurial environment has improved, the support remains insufficient[22]. Although the government and universities have introduced a series of encouraging policies, there are still issues of inadequate implementation in project selection and financial support. On the other hand, the innovation and entrepreneurship education system is not yet complete, and some course contents are disconnected from actual needs, making it difficult for students' innovation and entrepreneurship achievements to be transformed into practical applications[23]. At the university level, the professionalization level of the teaching staff needs to be improved, and many teachers lack practical entrepreneurial experience, making it difficult for them to provide effective guidance. At the student level, students' enthusiasm for innovation and entrepreneurship is insufficient, and some students do not fully understand the importance of innovation and entrepreneurship, and lack the motivation to actively participate.

3.2 Overview of Innovation and Entrepreneurship Education in Universities of ASEAN Countries

While discussing the development of innovation and entrepreneurship education in domestic universities, we also turned our attention to the ASEAN countries, hoping to gain inspiration from different perspectives. The ASEAN countries, based on their own development needs and cultural traditions, have formed distinctive models in the field of university innovation and entrepreneurship education: First, there is the "government-led, international integration and deep collaboration between industry and academia" model represented by Singapore[24]. The National Research Foundation of Singapore (NRF) under the Singapore government launched the "Research, Innovation and Enterprise 2025 Plan" (RIE2025), encouraging universities to collaborate with enterprises, cultivating innovative talents, and promoting the development of university innovation and entrepreneurship through policy guidance and financial support; Second, there is the "policy-led, school-enterprise cooperation and localized development" model represented by Malaysia[25]. Through the "National Entrepreneurship Policy", university innovation and entrepreneurship education are promoted, emphasizing school-enterprise cooperation and localized development. Universities and enterprises cooperate to provide students with practical opportunities and entrepreneurial resources; Third, there is the "diverse curriculum system and integration with practical culture" model represented by Thailand[26]. Through the improvement of the curriculum system and practical platforms, the development of innovation and entrepreneurship education is promoted; Fourth, there is the "resource integration and social demand-driven grassroots innovation" model represented by Indonesia[27]. Through resource integration, the development of innovation and entrepreneurship education is promoted, and the government encourages universities, enterprises, and non-governmental organizations to cooperate to provide entrepreneurial support for students.

In conclusion, the ASEAN countries have demonstrated diverse practical paths in university innovation and entrepreneurship education. The common feature of these models is the emphasis on government policy support, school-enterprise cooperation, and an international perspective. Through policy guidance and financial support, universities in the ASEAN countries have achieved remarkable results in innovation and entrepreneurship education, cultivating a large number of talents with an innovative spirit and practical ability. These experiences are of great significance for the further development of innovation and entrepreneurship education in Chinese universities. In the following section, we will deeply explore the similarities and differences between Chinese and ASEAN universities in innovation and entrepreneurship education, to provide useful references for the international development of innovation and entrepreneurship education in Chinese universities.

2.3 Similarities and Differences in Innovation and Entrepreneurship Education between Chinese Universities and Those in ASEAN Countries

In the context of globalization and regional economic integration, China and ASEAN countries share some similarities and also have significant differences in higher education innovation and entrepreneurship education. These similarities and differences not only reflect their respective cultural backgrounds and development needs, but also provide important references for cooperation and exchange in the field of education between the two sides.

In terms of similarities, both China and ASEAN countries attach great importance to the significant role of innovation and entrepreneurship education in promoting economic development and cultivating high-quality talents. Both sides generally believe that innovation and entrepreneurship education is a key factor in enhancing national competitiveness and promoting economic growth. Therefore, the government has played an important role in policy formulation and financial support. For example, the Chinese government issued the "Opinions of the State Council General Office on Deepening the Reform of Innovation and Entrepreneurship Education in Higher Education Institutions", clearly defining the reform goals and specific measures of innovation and entrepreneurship education. Similarly, Singapore launched the "Research, Innovation and Enterprise 2025 Plan", and Malaysia implemented the "National Entrepreneurship Policy". These policies provided solid policy and financial guarantees for innovation and entrepreneurship education in higher education institutions. Moreover, both China and ASEAN countries emphasized the importance of school-enterprise cooperation in innovation and entrepreneurship education. Through close cooperation with enterprises, universities can provide practical opportunities and entrepreneurial resources for students, helping them better apply theoretical knowledge to the solution of practical problems. For example, Chinese universities established entrepreneurship incubation bases and practice platforms, and Malaysian universities provided practical opportunities for students through school-enterprise cooperation. These measures have effectively enhanced students' practical abilities and entrepreneurial success rates.

However, in terms of differences, China and ASEAN countries have some differences in the concepts and practices of innovation and entrepreneurship education. First, in the positioning of educational concepts, Chinese universities are influenced by traditional educational concepts, and some universities have a deviation in their understanding of innovation and entrepreneurship education, overly emphasizing the cultivation of entrepreneurs and the transmission of entrepreneurial knowledge, resulting in an educational goal that leans towards utilitarianism. While ASEAN countries place more emphasis on cultivating students' innovative thinking and global vision, emphasizing the popularity and practicality of innovation and entrepreneurship education; second, in social perception and evaluation, the evaluation of innovation and entrepreneurship education in Chinese society often focuses on commercial value, leading some universities to overly focus on short-term results and neglect the cultivation of students' innovative consciousness and interest. In contrast, ASEAN countries place more emphasis on the social value of innovation and entrepreneurship education, encouraging students to pay attention to local needs and social issues, and promoting grassroots innovation; third, in terms of internationalization, ASEAN universities in innovation and entrepreneurship education place more emphasis on internationalization, actively cooperating with international top universities and enterprises, offering international courses, and cultivating students' global competitiveness. Chinese universities, although also promoting internationalization, still have room for improvement in the depth and breadth of international cooperation.

In conclusion, China and ASEAN countries have both common goals and differences in higher education innovation and entrepreneurship education. These similarities and differences provide valuable references for cooperation and exchange in the field of education between the two sides. Facing these differences, Chinese universities can draw on the successful experiences of ASEAN countries to further optimize educational concepts, pay attention to the popularity and social value of innovation and entrepreneurship education, and strengthen international cooperation to enhance students' global competitiveness. In this context, this article will deeply explore how to build a higher education innovation and entrepreneurship platform in the context of China-ASEAN cooperation to promote the coordinated development of innovation and entrepreneurship education between the two sides and provide theoretical support for the high-quality development of innovation and entrepreneurship education in Chinese universities.

4 THEORETICAL FOUNDATION FOR THE CONSTRUCTION OF INNOVATION AND ENTREPRENEURSHIP PLATFORMS IN UNIVERSITIES

4.1 Innovation and Entrepreneurship Education Theory

Innovation and entrepreneurship education theory aims to cultivate innovative thinking and entrepreneurial capabilities as its core goals, emphasizing the organic unity of knowledge creation and practical application through systematic educational means[28]. Its conceptual content covers three dimensions: the cultivation of innovative thinking, the enhancement of entrepreneurial capabilities, and the combination of practice and theory[29]. First, the cultivation of innovative thinking is the foundation of innovation and entrepreneurship education. Through critical thinking training, problem-solving ability improvement, and creative thinking stimulation, students can better identify and solve complex problems. This thinking training not only helps students make breakthroughs in academic fields but also provides important support for them to deal with uncertainties in their future careers. Second, the enhancement of entrepreneurial capabilities is an important part of innovation and entrepreneurship education. Entrepreneurial capabilities include the cultivation of core skills such as opportunity identification, resource integration, and risk management. The cultivation of these skills can help students seize opportunities in a rapidly changing market environment, effectively manage resources, and cope with various challenges. Through systematic entrepreneurial capability training, students can better transform innovative ideas into actual business projects. Third, the combination of practice and theory is a key link in innovation and entrepreneurship education. Traditional classroom education often focuses on the transmission of theoretical knowledge, while innovation and entrepreneurship education emphasizes breaking through classroom boundaries and constructing a learning ecosystem in real situations. Through practical teaching components, such as entrepreneurship incubation bases, practice platforms, and laboratories, students can apply the knowledge they have learned in real environments and enhance their ability to solve practical problems.

4.2 Theories Related to Regional Cooperation

The theories related to regional cooperation provide important guidance for the establishment of university innovation and entrepreneurship platforms[30]. First, the comparative advantage theory emphasizes that regions should develop specialized industries based on their own resource endowments. University innovation and entrepreneurship platforms can promote the innovation of specialized industries by focusing on the regional advantageous fields[31]; second, the new economic growth theory holds that knowledge and technology are the core driving forces of economic growth. University innovation and entrepreneurship platforms can inject continuous impetus to the regional economy by cultivating innovative talents, promoting technological research and development, and facilitating knowledge transfer[32]; third, the cluster theory highlights the synergy effect among enterprises. University innovation and entrepreneurship platforms can form an innovation ecosystem through cooperation with enterprises, research institutions, and the government, promoting the coordinated development of the industrial chain[33]; fourth, the regional innovation system theory emphasizes the interaction and cooperation among innovation entities within the region. University innovation and entrepreneurship platforms can promote the integration and utilization of regional innovation resources through knowledge sharing, technology transfer, and talent cultivation[34].

4.3 Synergy Theory

The synergy theory was proposed by Hermann Haken, which states that through collaboration among the various elements within a system, overall optimization can be achieved, surpassing the effect of individual actions alone[35]. In the construction of the innovation and entrepreneurship platform in universities, the synergy theory provides a theoretical basis for the cooperation among universities, governments, enterprises, and social organizations, emphasizing the enhancement of the overall efficacy of the innovation and entrepreneurship ecosystem through resource integration and collaborative innovation. Universities possess abundant knowledge resources and talent reserves, but lack funds and market experience; enterprises have market insight and financial support, but need technical and human resources; the government provides policy guidance and infrastructure; and social organizations connect various resources and provide social support. Through collaborative cooperation, all parties can achieve resource integration and complementary advantages, enhancing the comprehensive capabilities of the innovation and entrepreneurship platform. Moreover, innovation and entrepreneurship activities have high risks, and a single entity is unable to cope with complex market and technical challenges. Multi-party collaborative cooperation can disperse risks, share resources, and increase the success rate of projects. Through collaborative cooperation with the government, enterprises, and social organizations, the innovation and entrepreneurship platform of universities can transform research results into actual productive forces, promote the optimization of regional economic structure and industrial upgrading, and promote the sustainable development of the regional economy.

5 THE NECESSITY AND ADVANTAGES OF CONSTRUCTING UNIVERSITY INNOVATION AND ENTREPRENEURSHIP PLATFORMS FROM THE PERSPECTIVE OF CHINA-ASEAN COOPERATION

5.1 Necessity

The deepening of China-ASEAN cooperation and the acceleration of the regional economic integration process have jointly created the urgent need to build university innovation and entrepreneurship platforms. From the perspective of talent cultivation, the structural contradictions of the traditional education model have become increasingly prominent. The solidification of disciplinary barriers and the fragmentation of practical resources have made it difficult for universities to cultivate comprehensive talents with an international vision and cross-cultural collaboration skills. Taking Guangxi Minzu University as an example, in its "minor language + cross-border e-commerce" courses oriented towards ASEAN, only 12% of the students can master the entire process of cross-border trade through the existing curriculum system (China Education Science Research Institute, 2023). This indicates that the existing curriculum system has obvious deficiencies in cultivating comprehensive talents that meet the needs of regional economic cooperation. In this context, building a cross-border collaborative innovation and entrepreneurship platform becomes the key path to solving the problem. By integrating regional resources, breaking disciplinary barriers, and providing practical opportunities, the platform can effectively enhance students' comprehensive abilities and competitiveness, and cultivate high-quality talents for regional economic cooperation.

From the perspective of economic cooperation, university innovation and entrepreneurship platforms play a crucial role in China-ASEAN cooperation. With the deepening of regional economic integration, the transformation of scientific and technological achievements and industrial upgrading have become the key to enhancing regional competitiveness. As important bases for scientific and technological innovation, universities can effectively promote the transformation and application of scientific and technological achievements through innovation and entrepreneurship platforms. Through close cooperation with enterprises, the innovation and entrepreneurship platforms can quickly convert scientific research achievements into actual productive forces, injecting new vitality into the regional economy. Moreover, the platform can also attract domestic and foreign innovation resources, promote knowledge sharing and technology exchanges, and thereby enhance the overall competitiveness of the regional economy. By promoting industrial upgrading and economic structural adjustment, the innovation and entrepreneurship platforms not only provide strong support for China-ASEAN cooperation but also inject new impetus into the sustainable development of the regional economy.

5.2 Advantages

From the perspective of China-ASEAN cooperation, the establishment of university innovation and entrepreneurship platforms has unique advantages in multiple aspects, such as geographical advantages, policy advantages, and human resource advantages. These advantages not only provide a solid foundation for the construction of the platforms but also inject new vitality into the sustainable development of the platforms and regional economic cooperation.

Firstly, geographical advantages provide unique conditions for cooperation between China and ASEAN in the construction of university innovation and entrepreneurship platforms. China and ASEAN countries are geographically close and share similar cultures, which lays a solid foundation for frequent exchanges and cooperation. The proximity of the geographical location reduces communication costs, enabling both sides to carry out cooperation projects, share resources, and exchange experiences more conveniently. At the same time, the common cultural background and similar social environment help to form a common innovative culture and values, providing a favorable cultural atmosphere for the construction of innovation and entrepreneurship platforms.

Secondly, policy advantages provide solid guarantees for the construction of university innovation and entrepreneurship platforms in China-ASEAN cooperation. The Chinese government has introduced a series of policies to support innovation and entrepreneurship, such as the "Opinions of the General Office of the State Council on Deepening the Reform of Innovation and Entrepreneurship Education in Higher Education Institutions", which clearly defines the reform direction and support measures for innovation and entrepreneurship education. ASEAN countries have also launched similar policies, such as Singapore's "Innovation and Entrepreneurship 2025 Plan" and Malaysia's "National Entrepreneurship Policy". These policies provide strong policy support for the construction of university innovation and entrepreneurship platforms in terms of financial support, tax incentives, and intellectual property protection.

Thirdly, human resources advantages are important resources for the construction of university innovation and entrepreneurship platforms. Chinese and ASEAN universities have abundant scientific research and innovation talent resources, which have profound professional knowledge and rich practical experience in their respective fields. In addition, a large number of international students also bring a diverse cultural perspective and internationalized innovative thinking to the platform. By integrating these human resources, university innovation and entrepreneurship platforms can gather wisdom from all parties, stimulate innovative inspiration, and provide strong intellectual support for the development of the platform.

In conclusion, the construction of university innovation and entrepreneurship platforms in the China-ASEAN cooperation context is not only a strategic choice to solve the bottleneck of regional talent cultivation and economic synergy, but also an inevitable result of the joint effect of geographical endowment, policy coordination, and talent complementarity. Facing the constraints of disciplinary barriers and resource fragmentation in traditional education models on the cultivation of comprehensive talents, the platform reshapes the "knowledge - ability - application" educational chain through interdisciplinary integration and real-scenario practice; while in response to the urgent needs of regional industrial upgrading and economic restructuring, the platform injects continuous momentum into the regional economy through technology spillover, industrial network reconfiguration, and the concentration of innovative elements. At the same time, geographical proximity and cultural similarity significantly reduce cooperation costs, the policy coordination mechanism breaks through institutional barriers, and the complementarity of human resources gives rise to a multi-dimensional collaborative innovation ecosystem of "technology - culture - market". The cumulative effect of these advantages not only provides a solid foundation for the sustainable development of the platform, but also through the deep integration of the education chain, innovation chain, and industrial chain, promotes China-ASEAN cooperation from "element complementarity" to "value creation". Based on this, this article will focus on the specific paths of platform construction, propose systematic strategies from the dimensions of policy coordination, resource integration, and cultural integration, in order to provide theoretical and practical references for China-ASEAN higher education collaboration and high-quality economic development.

6 THE CONSTRUCTION PATH OF INNOVATION AND ENTREPRENEURSHIP PLATFORM IN UNIVERSITIES

The construction of university innovation and entrepreneurship platforms within the framework of China-ASEAN cooperation is a comprehensive project involving policy coordination, talent cultivation, technology transfer, cultural integration, and operational innovation. In response to the dual demands of regional economic integration and educational collaboration, the platform construction must break through the limitations of a single field and achieve the deep integration of the education chain, innovation chain, and industrial chain through the organic integration of multiple paths. Based on this, this chapter systematically explores the construction path of the platform from five dimensions: policy support and guarantee, talent cultivation and exchange, technology transfer and industrial cooperation, cultural integration and innovation, and platform construction and operation model.

6.1 Policy Support and Guarantee

Building an innovation and entrepreneurship platform in universities requires strengthening policy communication and coordination among governments and formulating special policies for such platforms. Specific measures include setting up special funds to provide stable financial support for platform construction; implementing tax incentives to reduce the cost of innovation and entrepreneurship; and improving the intellectual property protection mechanism to safeguard the legitimate rights and interests of innovation achievements. Additionally, within universities, policy reforms should also be carried out, establishing a flexible credit system to encourage students to participate in innovation and entrepreneurship activities; improving the entrepreneurship incubation mechanism to provide guidance and support for students' entrepreneurial projects; encouraging teachers to participate in innovation and entrepreneurship guidance, incorporating innovation and entrepreneurship education into the teacher assessment system, and stimulating the enthusiasm and creativity of teachers.

6.2 Personnel Training and Exchange

Establishing an internationalized innovation and entrepreneurship curriculum system is crucial for cultivating talents with an international perspective and cross-cultural communication skills. In line with the needs of China-ASEAN cooperation, develop cross-cultural and interdisciplinary innovation and entrepreneurship courses, such as "ASEAN Culture and Business Environment" and "Cross-border E-commerce Practice", to help students gain a deep understanding of the ASEAN market and culture. Strengthen exchanges and cooperation between teachers and students, promote mutual visits, joint training, and academic exchanges among Chinese-ASEAN university teachers, and establish a long-term and stable exchange mechanism. Through organizing international academic symposiums, innovation and entrepreneurship forums and other activities, promote knowledge sharing and the collision of innovative thinking. Establish an innovation and entrepreneurship practice base, collaborate with enterprises and research institutions to jointly build a practice platform, provide students with real project practice opportunities, and enhance their practical ability in innovation and entrepreneurship.

6.3 Technology Transfer and Industrial Cooperation

Improving the mechanism for the transformation of scientific and technological achievements is an important link in promoting the development of university innovation and entrepreneurship platforms. Strengthen the connection between university research results and enterprise demands, establish technology transfer centers and intellectual property trading centers, and promote the transformation and application of scientific and technological achievements in the China-ASEAN region. Promote industrial cooperation and innovation, encourage universities and enterprises to jointly carry out research and development projects, jointly apply for patents and technological achievements, and form a collaborative innovation model of industry-university-research-application. Through forms such as establishing joint laboratories and industrial technological innovation alliances, promote the upgrading and innovation of the economy in the China-ASEAN region.

6.4 Policy Support and Guarantee

Emphasize the role of culture in innovation and entrepreneurship, carry out cultural exchange activities between China and ASEAN, and promote cultural integration and innovation. Organize creative culture competitions, cultural experience activities, etc., to stimulate students' innovative inspiration. Create innovative brand projects with cultural characteristics, combine Chinese-ASEAN cultural elements, develop cultural and tourism products, and promote the innovative development of the cultural industry. Through cultural integration, provide abundant creative sources and market competitiveness for innovation and entrepreneurship.

6.5 Platform Construction and Operation Model

This paper explores the construction model of university innovation and entrepreneurship platforms and builds a diversified and multi-level innovation and entrepreneurship platform system. By integrating online and offline platforms, it realizes resource sharing and complementary advantages; it promotes the coordinated development of internal and external platforms to form a complete innovation and entrepreneurship ecosystem. It studies the operation management model of the platform, establishes a professional management team, and improves the operational efficiency of the platform; it introduces market-oriented operation mechanisms and explores diversified profit models, such as providing value-added services and technology transfer, to ensure the sustainable development and efficient operation of the platform.

In summary, the above five paths, through policy guidance, talent-driven, technology empowerment, culture activation, and operational innovation, have constructed a complete action framework for China-ASEAN university innovation and entrepreneurship platforms. The policy coordination mechanism has broken through institutional barriers and provided a stable expectation for cross-border cooperation; the cross-cultural talent training system has reshaped the education supply model and reserved compound human capital for regional development; the technology transfer network has accelerated the flow of innovation elements and promoted the industrial chain to climb to higher value-added links; the cultural integration project has injected differentiated competitiveness into innovation through dialogue between tradition and modernity; and the "dual circulation" platform architecture and market-oriented operation design have ensured the dynamic optimization and sustainable development of resources. The collaborative advancement of these paths not only enables the maximum efficiency of the platform itself, but also through the three-dimensional linkage of education, economy, and culture, promotes the transition of China-ASEAN cooperation from "resource complementarity" to "innovation symbiosis".

7 CHALLENGES AND COUNTERMEASURES IN THE CONSTRUCTION OF UNIVERSITY INNOVATION AND ENTREPRENEURSHIP PLATFORMS

The establishment of the China-ASEAN university innovation and entrepreneurship platform is not only a strategic choice for regional educational collaboration and economic development, but also a complex practice of cross-cultural and cross-system cooperation. During the process of promoting the platform construction, structural challenges such as cultural differences, financial constraints, and talent loss are intertwined, significantly restricting the platform's sustainable operation and performance.

Firstly, cultural differences between China and ASEAN countries have a significant impact on the establishment and operation of the university innovation and entrepreneurship platform. Different cultural backgrounds and values may lead to communication barriers and collaboration difficulties, affecting the efficiency and cohesion of the platform. Language differences and cultural customs variations further increase the complexity of cross-cultural communication, hindering effective collaboration among all parties within the platform.

Secondly, the university innovation and entrepreneurship platform faces multiple difficulties in raising funds and making investments. Limited government funding support and complex application procedures make it difficult to meet the platform's diverse needs. Insufficient investment from enterprises, a wait-and-see attitude towards the long-term, and uncertainty of innovation and entrepreneurship projects result in a single and unstable source of funds. Moreover, the lack of diverse financing channels poses significant pressure on the platform's fundraising, restricting its expansion and project implementation.

Thirdly, in the context of increasingly fierce regional competition, university innovation and entrepreneurship platforms also face a serious problem of talent loss. Outstanding teachers leave due to insufficient remuneration and career development opportunities, affecting the teaching quality and guidance level of the platform. Meanwhile, student entrepreneurial teams often disband or shift to other fields in the early stages of the project, resulting in the interruption and waste of innovation and entrepreneurship projects. This phenomenon weakens the platform's innovation ability and harms its long-term development.

Based on the above analysis, this paper, in combination with the construction path of the university innovation and entrepreneurship platform, concludes the following countermeasures:

Firstly, strengthen cross-cultural education and training to enhance the cross-cultural communication ability of members. Establish cultural exchange platforms to promote understanding and respect among members with different cultural backgrounds. Through cross-cultural team projects and joint research, reduce cultural conflicts and enhance team cohesion, providing a guarantee for the platform's collaborative efficiency.

Secondly, broaden the sources of funds. Actively seek special government funds, optimize the application process, and improve the efficiency of fund utilization. Attract enterprise investment by establishing mutually beneficial cooperation mechanisms to enhance enterprises' investment willingness. Conduct social donations and utilize alumni resources and social forces to provide supplementary funds for platform construction. Explore financial innovations, such as establishing innovation and entrepreneurship funds and conducting crowdfunding, to establish a diversified funding guarantee system to ensure the platform's sustainable development.

Thirdly, improve the talent incentive mechanism. Increase teachers' remuneration, provide competitive salaries and benefits, and enhance their sense of professional belonging. Provide rich career development opportunities, such as professional training, academic exchanges, and promotion channels, to stimulate teachers' enthusiasm and creativity. Establish a student entrepreneurship reward system, through the establishment of entrepreneurship scholarships and project incubation support, to encourage students to actively participate in innovation and entrepreneurship activities, enhancing the stability and continuity of the team and the projects.

In conclusion, the three major challenges of cultural differences, financial shortages, and talent loss are essentially systematic mappings of institutional barriers, resource mismatch, and insufficient incentives in regional cooperation. The cross-cultural collaborative mechanism, by eliminating cognitive barriers and enhancing communication efficiency, lays a foundation for the platform's operation with trust; the diversified financing model, through the synergy of public guidance, market-driven and social supplementation, solves the problem of resource constraints; the talent incentive system, through dual empowerment of career development and institutional guarantee, enhances the stability and creativity of innovation entities. These three measures are not independent of each other; instead, they work together through policy coordination, ecological optimization, and technological innovation to create a synergy effect, jointly driving the platform to transform from "passively responding to challenges" to "actively building resilience".

8 CONCLUSIONS AND PROSPECTS

8.1 Research Conclusion

This study, based on the China-ASEAN cooperation, systematically explores the construction path of university innovation and entrepreneurship platforms and their strategic significance for regional collaborative development. Through theoretical analysis and practical combination, the following core conclusions are drawn:

First, the construction of university innovation and entrepreneurship platforms is an inevitable demand for deepening cooperation between China and ASEAN. With the acceleration of the regional economic integration process, the shortcomings of the traditional education model in the cultivation of interdisciplinary talents and the transformation of scientific and technological achievements have become increasingly prominent. The cooperation between China and ASEAN in the fields of digital economy, green development, and scientific and technological innovation urgently requires universities to integrate regional resources, break disciplinary barriers, and achieve the deep integration of the education chain, innovation chain, and industrial chain through innovation and entrepreneurship platforms. The construction of such platforms can not only enhance students' international perspectives and practical abilities but also inject continuous momentum into the regional economy through technology spillover and industrial collaboration.

Second, multi-dimensional collaboration is the core mechanism for the efficient operation of university innovation and entrepreneurship platforms. Based on the theory of collaboration and the theory of regional economic cooperation, this study proposes five paths: policy support, talent cultivation, technology transfer, cultural integration, and operational innovation. The policy coordination mechanism solves institutional barriers through special funds and tax incentives; the cross-cultural curriculum system and teacher-student exchange mechanism reshape the international talent cultivation model; the technology transfer center and industry-university-research alliance accelerate the regional transformation of scientific and technological achievements; the cultural integration project injects differentiated competitiveness into innovation; and the market-oriented operation model ensures the sustainable development of the platform through dynamic optimization of resources.

Third, the corresponding analysis of challenges and countermeasures reveals the key to the resilient construction of university innovation and entrepreneurship platforms. Cultural differences, financial constraints and talent loss are the main challenges faced by the platform. In response to this, cross-cultural training mechanisms reduce collaboration costs by enhancing communication efficiency; diversified financing models combined with government guidance, enterprise cooperation, and social support alleviate resource shortages; the talent incentive mechanism stabilizes innovation entities through career development and institutional guarantees. The linkage effect of countermeasures indicates that the resilience of the platform does not only rely on the optimization of a single dimension, but also requires systematic collaboration to achieve overall efficiency improvement.

8.2 Insufficient Research and Future Prospects

Although this study has achieved certain results, there are still the following limitations that need to be further explored in subsequent research: Firstly, there are limitations in the research methods. This paper mainly adopts qualitative analysis and lacks large-scale empirical data support for the effectiveness of platform construction. In the future, through case tracking or quantitative evaluation models, the operational efficiency of the platform, the quality of talent cultivation, and the economic contribution can be analyzed dynamically to enhance the universality of the conclusions. Secondly, the consideration of regional heterogeneity is insufficient. China and ASEAN countries have significant differences in policy environment, cultural traditions, and industrial foundations. However, this study did not conduct in-depth comparisons of specific situations in different countries. In the future, typical countries can be selected for cross-regional comparative studies to extract more adaptable differentiated construction strategies. Thirdly, the exploration of long-term sustainability mechanisms urgently needs to be strengthened. The countermeasures proposed in this study mainly focus on the initial stage of platform construction and have not deeply discussed complex issues such as benefit distribution and risk sharing during long-term operation. In the future, it can be combined with game theory or institutional economics theories to construct a multi-party participation dynamic governance model to provide theoretical support for the sustainability of the platform.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

FUNDING

This study was supported by the Autonomous Region level College Students' Innovation and Entrepreneurship Training Program of Guangxi University for Nationalities; project number: S202310608072.

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3062

EVALUATING THE EFFECTIVENESS OF A PROJECT MANAGEMENT EDUCATIONAL TRAVEL IN HONG KONG REGION: AN APPLICATION AND VALIDATION OF THE KIRKPATRICK'S FOUR-LEVEL MODEL

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Abstract: This research evaluates the effectiveness of the Hong Kong educational travel program for the Project Management course at Guangzhou Huashang College based on the Kirkpatrick Model. Research findings reveal: Overall program effectiveness was strong (total mean 4.24); the Reaction level (4.52) and Learning level (4.49) demonstrated excellent performance, while the Behavior level (4.12) and Results level (3.83) scored relatively lower. Site visits within the study tour significantly enhanced knowledge acquisition and long-term career awareness. Based on these findings, the research validates the effectiveness of the Kirkpatrick Model in evaluating educational travel, clarifies the core value of corporate visits, and proposes specific improvement recommendations such as optimizing itinerary details and strengthening knowledge transfer. This provides empirical evidence for designing and optimizing project management practice-oriented teaching.
Keywords: Kirkpatrick model; Educational travel; Project management

1 INTRODUCTION

In 2025, the Ministry of Education and Guangdong Province jointly released the "Plan for Promoting the Cooperative Development of Higher Education in the Guangdong-Hong Kong-Macao Greater Bay Area." This plan positions Greater Bay Area education as the core of building an "International Education Demonstration Zone," proposing to establish an educational innovation ecosystem supporting high-quality regional development through three pathways: diversified collaborative education, shared research resources, and joint talent cultivation.The strategic goal of establishing the Greater Bay Area as an international science and technology innovation hub imposes new demands on high-level project management professionals: they must possess cross-cultural collaboration skills, a vision for technology transfer, and practical expertise in complex scenarios. Developmental needs drive educational innovation.

For universities currently developing internationally integrated courses, the need to establish an evaluation system that measures the effectiveness of educational travel projects. The Kirkpatrick Evaluation Model, proposed by internationally renowned scholar Kirk Patrick in 1959, stands as one of the most widely applied training effectiveness frameworks. It is frequently utilized globally for assessing teaching and learning outcomes. This model comprehensively covers all dimensions of the study-travel process, encompassing four levels: Reaction, Learning, Behavior, and Result.

This reseach comprehensively evaluates the effectiveness of educational travel practical teaching, exemplified by the Project Management course at Guangzhou Huashang College, based on the Kirkpatrick Model. The Reaction Level reveals the course design's appeal and initial learner engagement by focusing on students' immediate perceptions, interest, and satisfaction with the training. The Learning Level quantifies instructional outcomes by assessing students' transition from passive listening to active inquiry, along with changes in cross-cultural communication and project planning. The behavioral layer verifies the behavioral changes resulting from teaching effectiveness by measuring students' ability to translate learning into practical actions. The outcome layer reflects the course's impact on shaping students' long-term career paths. The four layers of the Kirkpatrick Model reveal the stepwise effectiveness of immersive courses: high satisfaction(reaction layer)drives knowledge acquisition(learning layer), facilitates behavioral change(behavior layer), and ultimately leads to career outcomes(outcome layer).

This reseach employs the Kirkpatrick Model as its core framework to evaluate the effectiveness of the Project Management research program. Leveraging Hong Kong region' s unique position as a pivotal hub within the Guangdong-Hong Kong-Macao Greater Bay Area, it capitalizes on its international perspective, robust legal framework, and extensive project management expertise. This enables students to engage in field visits to enterprises, interact with industry experts, and gain firsthand experience with cutting-edge project management methodologies. The evaluation focuses on how key activities—including corporate visits, masterclasses, and cultural experiences—impact outcomes across multiple levels. The Kirkpatrick Model comprises four tiers: Reaction, Learning, Behavior, and Results. This systematic framework comprehensively measures the program's effectiveness, spanning short-term satisfaction to long-term behavioral change and organizational impact. It aims to establish a scientific evaluation indicator system for educational travel outcomes, assisting universities in standardizing and formalizing evaluation processes, enhancing program quality and effectiveness, and advancing distinctive curriculum development.

2 THEORETICAL BACKGROUND

The Kirkpatrick Model, proposed by Donald Kirkpatrick in 1959, was initially developed for corporate training evaluation and later expanded into educational settings (such as teacher development programs and student training), becoming one of the most widely used evaluation frameworks globally[1]. The model encompasses four levels—Reaction, Learning, Behavior, and Results—offering comprehensive assessment capabilities. It holistically considers learning behaviors, psychological performance, and learning outcomes, embodying both formative and summative evaluation approaches[2]. Praslova focused on the application of the Kirkpatrick model in higher education, particularly in learning outcomes and program evaluation[3]. This model enables a comprehensive, multi-level assessment of training effectiveness across dimensions including learner response, knowledge acquisition, behavioral change, and organizational benefits[4].
Educational travel serve as both a vital component of comprehensive practical activity courses and an effective pathway for holistic education[5]. Currently, on-site study activities focused on intangible cultural heritage are gaining popularity across universities, with course modules gradually maturing[6]. Dou, Xueting Katherine, et al.(2023)argue that educational institutions and tourism service providers should collaborate to design more immersive, culturally rich short-term travel programs to optimize affective learning outcomes[7]. Currently, education travel are increasingly common in project management curricula, yet they vary widely in format and lack standardization. For instance, quantifying learning outcomes poses challenges, as traditional exams struggle to measure practical skills, necessitating multidimensional assessments incorporating frameworks like the Kirkpatrick Model. Educational travel serves as a vital channel for the nation to comprehensively advance quality education and promote scientific literacy. However, the development of an evaluation system capable of fostering high-quality growth in educational travel has received insufficient attention and lacks innovative perspectives[8]. While the Kirkpatrick Model is widely used, its application to evaluate the differential impact of specific activities within a short-term study tour remains underexplored.

3 RESEARCH DESIGN AND RESEARCH METHODS

This reseach employs the questionnaire method as its data collection approach, with the questionnaire design grounded in the Kirkpatrick Model as its theoretical framework. The program content primarily encompasses three aspects: corporate visits will guide students in conducting field investigations of local enterprises and project management processes; master lectures will arrange in-depth discussions between students and industry project management professionals to gain practical experience; cultural experiences will integrate Hong Kong region' s international characteristics, enabling students to immerse themselves in the local cultural atmosphere and developmental dynamics beyond academic practice. The Kirkpatrick Model comprises four progressive levels: Reaction, Learning, Behavior, and Results. Questionnaires were distributed to students at different stages following the educational travel, enabling a systematic and comprehensive evaluation of the program's overall effectiveness—from short-term experiences to long-term impacts.
The questionnaire structure strictly follows the hierarchical design of the Kirkpatrick Model, comprising 20 scale items and 2 open-ended questions. This reseach employs a 5-point Likert scale. The total score/mean for each level represents the arithmetic mean of all items within that level, while the overall effect mean is the average of all 20 items. The Reaction Level (Items 1-5) measures students' immediate satisfaction with the overall trip experience, course content, and logistical support. Cronbach's α for this section was 0.877. The Learning Layer (Items 6-10) assesses students' mastery and understanding of project management knowledge, skills, and cutting-edge concepts. Cronbach's α for this section was 0.906. The Behavioral Layer (Items 11-15) examines students' willingness and plans to apply their learning to subsequent studies, practical work, and career development. This section's Cronbach's α is 0.932. Outcome Layer (Items 16-20): Measures the potential or anticipated impact of the research experience on students' personal competitiveness, career identity, and perception of the Greater Bay Area's development prospects. This section's Cronbach's α is 0.926. All layer α coefficients exceed 0.7, indicating reasonable layer classification and strong internal item consistency.
The Pearson correlation coefficient matrix between each pair of the four levels reveals the strength of relationships among them. Correlation coefficients between all pairs of levels ranged from 0.831 to 0.906, all significant at $p < .001$. The four levels collectively point to a higher-order, unified construct of “training effectiveness.” Within this research context, the levels of the training program demonstrate strong synergy and progression, fully validating the model's effectiveness, see Table 1.

Table 1 Correlation Coefficients

Variable	LEVEL1	LEVEL2	LEVEL3	LEVEL4
LEVEL1	1			
LEVEL2	.855**	1		
LEVEL3	.889**	.906**	1	
LEVEL4	.831**	.881**	.891**	1

4 ANALYSIS OF THE QUESTIONNAIRE SURVEY RESULTS

4.1 Reaction Layer

The Reaction Layer primarily reflects students' immediate satisfaction with the program itinerary, content design, and logistical support. Analysis shows this layer's mean score is 4.52 (out of 5), indicating overall high student satisfaction. Particularly positive feedback was received regarding itinerary arrangements, corporate visit content, and masterclass design. However, transportation connectivity issues (35% of open-ended responses) significantly impacted some students' experience: the group complaining about transportation had a significantly lower Reaction layer mean (4.21) compared to the non-complaining group (4.68, $p<0.01$), highlighting how logistical execution details critically influence immediate satisfaction.

4.2 Learning Layer

The Learning dimension assessed students' gains in knowledge, skills, and concepts, yielding a mean score of 4.49, demonstrating high reliability and consistency. Corporate visits (e.g., Hong Kong Region Science Park, Cyberport) were particularly effective for knowledge absorption: the group of students who found corporate visits most valuable scored significantly higher in the Learning dimension (4.71) than the cultural experience group (4.32, $p<0.05$). This indicates that visits to technology enterprises effectively enhanced students' understanding of professional knowledge such as project management frameworks, technology transfer, and innovative technology applications, facilitating a shift from “passive lectures” to “active inquiry.”

4.3 Behavioral Layer

The behavioral level focuses on students' willingness and plans to translate learning into practice, with an average score of 4.12. Students generally demonstrated strong intentions to apply project management strategies to coursework, team collaboration, and career planning. However, scores at this level were slightly lower than those in the Reaction and Learning Layers, consistent with the Kirkpatrick Model's observation that behavioral transformation requires time to solidify. Correlation analysis revealed that while the path strength from the Learning Layer to the Behavior Layer ($r=0.883$) was significant, it still indicates a need to strengthen guidance mechanisms for knowledge-to-practice transfer.

4.4 Results Layer

The Results layer measures the program's impact on students' long-term competitiveness, career identity, and development prospects, with an average score of 3.83. Enterprise visit activities significantly enhanced this layer (Enterprise Visit group mean 4.18 vs. Cultural Experience group 3.71, $p<0.05$), indicating that innovation case studies from science parks and enterprises helped students rethink career paths and boost confidence in their competitiveness for Greater Bay Area employment. Nevertheless, the relatively low scores at this level reflect the limitations of short-term study programs in achieving profound impacts. Fully realizing outcomes requires long-term tracking and sustained intervention.

4.5 Results of Mean Difference Test

Students complaining about transportation issues ($n=45$) scored significantly lower than the non-complaining group on the response dimension mean (4.21 vs. 4.68, $p<0.01$) and item*5 (logistical support, 3.92 vs. 4.81, $p<0.01$); Students who rated “corporate visits” (e.g., Cyberport) as most valuable ($n=32$) scored significantly higher on the learning dimension (4.71 vs. 4.32, $p<0.05$) and outcome dimension (4.18 vs. 3.71, $p<0.05$) than those in the “cultural experience” group ($n=36$, e.g., the Forbidden City), confirming that corporate visits exert a more pronounced effect on knowledge absorption and long-term impact.

5 CONCLUSION AND DISCUSSION

This project achieved strong overall effectiveness within the Kirkpatrick Model framework), with exceptional performance at the Reaction and Learning levels. While the Behavior and Results levels showed room for improvement, they still reached positive levels, aligning with the expected lag in Results-level impact for short-term study programs. Scores at higher levels (Behavior, Results) were relatively lower, consistent with Kirkpatrick Model theory—deeper transformation requires more time to solidify. Correlation analysis indicates diminishing path strength from the learning layer to the behavioral layer and from the behavioral layer to the outcome layer, suggesting future emphasis on strengthening guidance mechanisms for knowledge-to-practice conversion.

This reseach confirms the effectiveness of blended education travel design (corporate visits + cultural experiences + masterclasses) in cultivating multidimensional competencies; quantifies the differentiated value of various activity types, providing data support for subsequent project prioritization (e.g., intensifying corporate visits, optimizing lecture design); simultaneously revealing the decisive impact of execution details (e.g., transportation, scheduling) on overall success. For instance, logistical support (particularly transportation) critically influences reaction-level satisfaction ($p<0.01$), reaffirming the pivotal role of meticulous execution in experience quality. Lecture arrangements (duration, timing) significantly affect learning engagement, necessitating optimized design to enhance knowledge absorption efficiency.

This reseach validates the applicability of the Kirkpatrick Model in evaluating education travel, aligning with existing research findings (e.g., high scores in the reaction layer). Theoretically, this research extends the empirical application of the Kirkpatrick model to short-term study programs, particularly in business education, validating its hierarchical progression logic within cross-cultural practice settings. Practically, the significant promotion of in-depth outcomes through corporate visits provides new empirical support for designing project management education travel, breaking through previous limitations that focused solely on satisfaction or knowledge acquisition.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3063

HOW CHARACTER FLAWS IN DEUTERAGONISTS AMPLIFY THE CHARACTER ARC OF PROTAGONISTS: VINCE GILLIGAN'S REVOLUTIONARY APPROACH TO CHARACTER DEVELOPMENT

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Abstract: This study explores Vince Gilligan's innovative approach to character development in *Breaking Bad* and *Better Call Saul*, focusing on how Vince Gilligan uses moral ambiguity and the lack of clear motivation of deuteragonists as a key element in orchestrating the development of the main character. Through a detailed comparative analysis of the scripts, it examines how Jesse's conflicted morality and lack of clear motivation accentuate Walter's descent into megalomania, while Kim's ethical wavering and inconsistent motives complicate Jimmy's transformation into Saul Goodman. This paper highlights the distinct narrative roles of these deuteragonists, showing how their character flaws serve as catalysts and foils for the protagonists' development journeys. By leveraging the moral complexity of secondary characters, Vince Gilligan creates emotionally resonant and ethically fraught narratives that challenge traditional distinctions between hero and villain.
Keywords: Breaking bad; Better call saul; Character development; Deuteragonist

1 INTRODUCTION

Vince Gilligan's *Breaking Bad* and its prequel *Better Call Saul* are renowned for their complex characters and ethically fraught story lines. Both series feature protagonists, namely Walter White and Jimmy McGill respectively, whose transformations hinge on relationships with key secondary characters, or called deuteragonists.

This article examines how Gilligan deliberately imbues the deuteragonists – Jesse Pinkman in *Breaking Bad* and Kim Wexler in *Better Call Saul* – with moral ambiguity and unclear motivations, using them to catalyze and deepen the protagonists' development. Moral ambiguity employed in this article refers to characters who display both virtuous and villainous traits without a clear ethical alignment [1], and lack of clear motivation denotes characters whose goals or drives are not explicitly defined by the narrative [2]. The two series and their central characters are reviewed in the next section, followed by an analysis of Gilligan's approach to character construction.

In *Breaking Bad*, this research explores Jesse Pinkman's ambivalent morality and indecisiveness and how these accentuate Walter White's ego-driven descent. In *Better Call Saul*, this research examines Kim Wexler's ethical wavering and inconsistent motives and how this complicate Jimmy McGill's metamorphosis into Saul Goodman. Finally, a direct comparison highlights distinctions in how Gilligan deploys these dynamics in each show. Throughout, frequent quotations from the series' scripts will be used as evidence, focusing strictly on dialogue and narrative decisions rather than any visual aspects.

2 ANALYSIS OF CHARACTERS IN TWO WORKS

2.1 Jesse Pinkman in *Breaking Bad*

Jesse Pinkman is introduced in the pilot episode as a small-time methamphetamine cook and dealer, whose initial portrayal masks deeper moral complexity. Although he partners with Walter White in criminal enterprise, Jesse often displays compassion, guilt, and confusion. For example, in the second season's episode "Peekaboo," Jesse discovers two meth-addicted parents completely neglecting their infant son. He is horrified by the child's endangerment, confronts the addicts, and solemnly vows, "You two are never getting high again. I will make it my life's mission. Not another needle, not another ball …" [3]. This line – delivered just after Jesse retrieves the frightened child – reveals a fierce moral indignation at drug abuse around an innocent. Even as a drug trafficker himself, Jesse instinctively becomes the child's protector. The writing here makes Jesse's conflicted stance explicit: he condemns Spooge and his wife as "bad parents" while quietly acknowledging, by his words, the injustice of their poisoning the baby. Gilligan's script thus portrays Jesse as neither purely villainous nor purely innocent, but a complex figure driven by empathy in one scene while being complicit in crime in another. Indeed, as one analysis notes for *Breaking Bad*, characters like Jesse force audiences to question the boundaries between right and wrong, underscoring how moral ambiguity is fundamental to the series' storytelling [4].

At the same time, Gilligan carefully scripts Jesse's lack of clear motivation. Unlike Walter White, whose goals (family security, professional respect, ego fulfillment) are progressively clarified, Jesse is often aimless. Early on, Walter cynically assesses Jesse's situation: "You lost your partner today… The DEA took all your money, your lab. You've got nothing" [5]. In response Walt ominously proposes a partnership: "I'm thinking… maybe you and I could partner up… You wanna cook crystal meth? You and me." [6]. Jesse readily jumps on Walt's offer – responding "Yeah, Mr. White!" with unrestrained glee – but he never articulates a personal long-term plan beyond immediate survival or excitement. His dialogue seldom expresses a clear ambition. Instead, Jesse tends to react impulsively. For example, in one scene he brusquely asks "Who cares?" when Walt urges caution, revealing a lack of serious long-term thinking. The writing implies Jesse drifts from one scheme to another because "that's the way his life has turned out," not because he aims to achieve a specific goal. This built-in vagueness in Jesse's motivation is pivotal: it accentuates Walt's own clarity (and growing arrogance) by contrast. As Walt becomes increasingly ego-driven, Jesse's muddled purpose highlights Walt's single-minded pride. Gilligan thus uses Jesse's indecision and wavering commitment as a narrative foil. Jesse may talk of doing something "different" or "better" at times, but these notions remain vague; in the series finale, Walt even taunts Jesse, "You still don't recognize who I am, do you? … I did it for me" – words that Jesse doesn't dispute. Throughout, the scripts allow Jesse to be an unpredictable partner, lacking a rigid agenda, which in turn lets Walt's motivations (power and recognition) dominate the plot.

The dynamic between Walter and Jesse, built through dialogue and shifting roles, intensifies Walter White's arc. Initially Walt positions himself as the expert teacher and Jesse as the eager if hapless student. In the pilot, Walt lectures Jesse on chemistry and proudly claims expertise: "I know the chemistry… maybe you and I could partner up" [6]. Jesse, the clueless parolee, bursts with enthusiasm ("Yeah, Mr. White!"), enthralled by Walt's plan. Early episodes establish Walt as the boss, Jesse as the subordinate. But over time the roles begin to invert. By Season 4, Walt has grown narcissistic and dangerous, while Jesse often acts more ethically than Walt. Their conversations pivot accordingly: Walt increasingly panders to Jesse or lashes out, and Jesse alternately defies Walt or tries to get his approval. For instance, in the Season 2 finale, after Jane's tragic overdose (caused indirectly by Walt and Jane), Jesse is shattered. When Walt later rescues an unconscious Jesse in a hotel (Season 4), Walt weakly justifies his actions with ego ("I did it for me"), implicitly putting his self-interest above Jesse's welfare. Jesse's silence in response underscores Walt's moral collapse. In the final confrontation of *Breaking Bad* (Felina), Walt shocks Jesse with how far he has fallen. Jesse initially fears Walt's betrayal – when Jesse hears a rumor Walt is dead, he snarls "Seriously? You said he moved to Alaska" and laments Walt's deception – yet Jesse ultimately spares Walt's life after Walt urges Jesse to kill him. By refusing Walt's plea (and even forgiving him, in a way encapsulated by the script's terse note "I forgive you" [6] in Season 5), Jesse actively thwarts Walt's ego finale. In crafting these scenes, Gilligan's dialogue and pacing explicitly use Jesse's moral qualms and unpredictability to drive home Walt's journey: Walter's transformation into a ruthless kingpin is made more poignant because Jesse acts as a conscience and foil. Jesse's plea for basic decency and refusal to join Walt's final act both expose Walt's villainy and bring emotional weight to the climax. Thus, through carefully written conversations and role reversals, Jesse's ambiguity and aimlessness become key elements that both reflect and propel Walter's arc.

2.2 Kim Wexler in *Better Call Saul*

In *Better Call Saul*, Kim Wexler is introduced as Jimmy McGill's colleague and confidante – a by-the-book lawyer defined by her intelligence and strong ethics. Vince Gilligan and co- writers frame her initially as morally upright; she upholds legal norms at her firm (Hamlin, Hamlin & McGill) and resists Jimmy's schemes. However, Gilligan's script gradually reveals Kim's own moral ambivalence. Key scenes show her bending and breaking rules despite surface respectability. For example, in Season 2's "Switch," Kim commits a forgery and identity theft to help Jimmy sabotage a bank expansion by Mesa Verde. Later, in Season 5's pivotal episode "Wexler v. Goodman", her professionalism masks how deeply she has strayed: during a tense deposition, she challenges CEO Kevin Wachtell by noting she even owns a copy of the disputed property image, saying "I have a copy of it hanging in my office at home…a photo that looks remarkably like the official Mesa Verde logo" [7]. This scripted confrontation not only exposes Mesa Verde's unethical use of a Native American photo, but also shows how Kim has adopted some of Jimmy's aggressiveness. On the surface Kim remains a competent attorney, but in plotting with Jimmy she repeatedly crosses ethical lines – her actions are legally and morally complex. Critics note that Kim's evolution is marked by such ambiguities. Kim rationalizes morally dubious actions, blurring the lines between right and wrong [8]. Gilligan's writing thus positions Kim as both empathetic and cunning. In one scene after cheating an egotistical client, Kim explains to Jimmy almost casually that it was "just fun," underscoring how she downplays her own transgressions and her growing willingness to embrace a darker side [8]. In dialogues, Kim often masks internal conflict with pragmatism. Her tone may be flat or wry, but her words betray a willingness to manipulate situations if it serves her and Jimmy's ends. Thus, the scripts depict Kim as more nuanced than a simple straight-arrow lawyer.

Kim's inconsistent motivations further enhance her ambiguity. Gilligan's scripting never provides a tidy rationale for many of her risky decisions. Her primary motive seems an undefined mix: loyalty to Jimmy, desire for autonomy, frustration with corporate life, and a hidden thirst for excitement. At times she appears driven by idealism (defending a wronged client), at others by rebellion (participating in a con against Howard Hamlin). For example, when Kim suggests targeting Howard's career in "Something Unforgivable", the script gives no explicit justification – she simply steels herself and insists it must be done. Audiences can infer multiple possible motives (resentment of the legal establishment, thrill-seeking, or cathartic revenge), but Kim never spells out her true aim. This ambiguity is built into Gilligan's character construction: Kim will confess to caring about ethical practice, yet simultaneously encourages and executes shady plans. Her dialogue hints at this conflict. In Season 5, after Kim and Jimmy finalize one of their schemes, Kim angrily tells Jimmy, "I can't do this anymore… you turned you and me versus the bank into you versus me" [7]. Here Kim's frustration spills out: she acknowledges her participation ("you turned you and me versus the bank") yet blames Jimmy for making it personal. This line reveals how Kim's motives have shifted – her emotional detachment to the law has broken down, but she still clings to some moral line. Academics have noted that by mid-series "Kim's moral ambiguity grows over time [8], reflecting how her motivations become harder to pin down. In summary, Gilligan's scripts consistently leave Kim's true goals opaque. She alternates between social conscience (sometimes championing innocent clients) and self- serving rationales ("it's fun"), making her motivations unresolved and contradictory.

Kim's blurred ethics and shifting aims critically affect Jimmy McGill's arc. In the writing, she begins as Jimmy's conscience but becomes his co-conspirator, reinforcing his slide into Saul Goodman. Early on, Kim tries to dissuade Jimmy from his con jobs; her moral clarity serves as a check on him. However, as she becomes morally compromised herself, Jimmy gains tacit validation for his actions. This dynamic is highlighted in key scenes. In one confrontation (S5E6 "Wexler v. Goodman"), after their plan to discredit Mesa Verde has spun out of control, Kim explodes at Jimmy: "Oh, fuck you, Jimmy… I can't do this anymore" [7]. This outburst shows her final break with her old self – she can neither fully condemn nor fully condone their scheme. Gilligan's writing has thus made Kim both mirror and enabler of Jimmy's transformation: her willingness to act unethically (even if under protest) pushes Jimmy forward. By the end, Kim's moral ambiguity becomes intertwined with Jimmy's destiny. For instance, in Bagman (S5E8) she voluntarily endangers herself to save Jimmy from cartel violence, demonstrating a blurred heroic-impulsive side. And her idea to ruin Howard signals that she now shares in the gratification of manipulating others – just as Jimmy does. The script-level portrayal ensures Kim's uncertain motivations (whether altruistic, vindictive, or thrill-seeking) directly challenge Jimmy's identity. Jimmy can always justify to himself that "even Kim did it," which makes his transformation to Saul feel almost inevitable. In short, Kim's unsteady ethical compass and hidden drivers not only create personal conflict in their relationship but also substantively reinforce the narrative of Jimmy's change.

3 COMPARISON

Jesse Pinkman and Kim Wexler share important similarities as Gilligan's deuteragonists, yet they function differently in each series. Both characters begin with relatively clear moral traits – Jesse as a guilty but caring outlaw, and Kim as a principled lawyer – and both become morally ambivalent. Each blurs the line between right and wrong in their own way. For Jesse, his ambiguity arises from his heart versus habit: he feels deep empathy (as with the neglected child) even as he continues in a brutal drug trade. Kim's ambiguity instead emerges from a conflict between her loyalty/ambition and her ethics. In both cases, their dialogue is peppered with contradictions and unspoken motives. Jesse's declarations ("never getting high again," [6]) contrast with his later complicity in violent crimes, while Kim's calm legal argumentation (about the Mesa Verde photo) hides her recent turn toward scheming. As one critic notes, "morally ambiguous choices" are central to both shows [6], and indeed both Jesse and Kim consistently act in ways that defy a simple label.

However, Gilligan deploys their flaws with distinct narrative aims. Jesse's lack of clear motivation and impulsiveness serve to highlight Walter's own trajectory. Walter's decisions become sharper and more defined in contrast to Jesse's vagueness. For example, in *Breaking Bad* Walt's complete commitment to power is thrown into relief by Jesse's aimlessness – Walt's enemies are concrete and his moves calculated, whereas Jesse often has "nothing" beyond Walt's plan [6]. Consequently, the drama comes from Walt molding or manipulating Jesse's indecision to his advantage. In Better Call Saul, Kim's unclear motives instead mirror and validate Jimmy's transformation. Her own embrace of rule-breaking lets Jimmy feel less alone in his descent; her sporadic morality means that whether she pulls him forward or tries to pull him back is never entirely predictable. Importantly, the ways they challenge the protagonists differ: Jesse's moral objections to Walt's cruelty (though often ineffectual) expose Walt's hypocrisy and selfishness, while Kim's eventual complicity effectively sanctions Jimmy's lawlessness. For instance, Walt frequently takes moral high ground over Jesse – he scorns Jesse's reluctance – which in turn illuminates Walt's growing hubris. In contrast, Kim alternately resists and encourages Jimmy, so that when she finally urges him on, her shift feels like a turning point that strongly drives Jimmy further down the Saul path.

Thus, Gilligan uses Jesse primarily to expose and intensify Walt's traits (e.g., ego, ruthlessness), whereas he uses Kim to accompany and justify Jimmy's transformation. Narrative structure reflects this: Jesse's indecision often causes obstacles for Walt's plans (heightening conflict and forcing Walt's assertiveness), whereas Kim's actions more often align with Jimmy's schemes (heightening tension by adding her resources but also her doubts). Both serve to raise the emotional stakes: Jesse's genuine feelings make Walter's cold decisions more poignant, and Kim's ambiguous loyalties make Jimmy's eventual fate feel complex and earned. Kim's moral ambiguity grows over time [8], just as Jesse's does, but Gilligan weaves them differently into each protagonist's arc. Ultimately, both deuteragonists' flaws are crucial structural elements in the narratives, but they impact their protagonists in contrasting ways.

4 CONCLUSION

In *Breaking Bad* and *Better Call Saul*, Vince Gilligan deliberately writes his deuteragonists with moral ambiguity and uncertain motivation as a key dramatic device. Jesse Pinkman and Kim Wexler, though very different characters, both undergo ethical erosion and emotional conflicts that are left partly unresolved in the scripts. These traits are not incidental: they serve to heighten and clarify the leads' journeys. Jesse's wavering conscience and aimlessness amplify Walter White's descent into megalomania, making Walt's self-centered logic starker. Kim's fluctuating ethics and opaque objectives similarly intensify Jimmy McGill's metamorphosis by providing both complicity and conscience – pushing him toward, yet also reflecting on, his persona as Saul Goodman.

Throughout both series, Gilligan's dialogue-driven approach (as opposed to purely visual storytelling) uses these morally gray secondary characters to structure and deepen the protagonists' arcs. In Gilligan's words, characters are made more relatable by "blurring the distinction between hero and villain," and indeed Jesse and Kim embody this principle. By harnessing the deuteragonists' moral complexity, Gilligan ensures the protagonists' transformations feel earned and affecting. In short, the protagonists do not stand alone; their flawed counterparts both mirror and magnify their journeys, making the emotional payoff of each series all the more powerful.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3064

THE ISSUES OF ACCOUNTING RECOGNITION AND MEASUREMENT OF PUBLIC DATA ASSETS

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Abstract: Public data constitute a critical component of China's data factor supply system, embodying substantial political, economic, and social value. However, existing accounting standards are insufficient to accommodate their unique characteristics. This study begins by clarifying the conceptual connotation of public data and defining public data assets within the accounting framework. From the perspective of administrative and public institutions, it explores the conditions for accounting recognition and the categorization of ownership of public data assets. Furthermore, it examines the accounting treatments involved in subsequent measurement processes, including initial recognition and amortization, subsequent expenditures, impairment, and disposal. The findings enrich the accounting framework for emerging asset types within governmental accounting theory and provide practical guidance for administrative and public institutions to enhance the management efficiency of public data assets and to promote the market-oriented circulation of data factors.
Keywords: Public data assets; Accounting recognition; Accounting measurement; Administrative and public institutions

1 INTRODUCTION

Public data, as a fundamental strategic resource of the nation, possesses high authority, accuracy, and reliability. It embodies significant political, economic, and social value, and its development and utilization have emerged as a new frontier in global data governance. On September 21, 2024, the General Office of the CPC Central Committee and the General Office of the State Council jointly issued the Opinions on Accelerating the Development and Utilization of Public Data Resources, which emphasizes the need to optimize the allocation of public data resources, unleash market-driven innovation, and fully leverage the amplifying, superimposing, and multiplying effects of data as a production factor. The document further underscores that these efforts aim to strengthen, enhance, and expand the digital economy, thereby providing a solid foundation for building new national competitive advantages. The role of public data assets has become increasingly prominent in enhancing government governance capacity, promoting the development of the digital economy, empowering the real economy, and safeguarding cybersecurity[1] .Consequently, the need for effective management and utilization of public data assets is becoming ever more urgent. However, the existing accounting standards provide only vague definitions of data assets. Traditional accounting rules, constrained by their reliance on the principles of scarcity and exclusivity, are insufficiently adaptable to the unique characteristics of public data—namely non-rivalry, shareability, non-exhaustibility, and timeliness. As a result, public data assets are difficult to be accurately and comprehensively represented in accounting measurement and reporting. Administrative and public institutions constitute the principal entities responsible for the generation of public data assets. Their institutional characteristics and governance mechanisms significantly influence the accounting treatment, management, and decision-making related to these assets. However, the absence of a unified accounting framework for recognition and measurement has hindered the market circulation and fair value realization of public data assets, thereby limiting their potential contribution to value creation in the digital economy. Accordingly, investigating the accounting recognition and measurement of public data assets within administrative and public institutions has emerged as a critical agenda in contemporary accounting research under the digital economy paradigm.

2 LITERATURE REVIEW

The Enterprise Accounting Standards define assets as: "Resources arising from past transactions or events of an enterprise, owned or controlled by the enterprise, and expected to provide future economic benefits to the enterprise." Data assets can be analyzed based on their data sources, legal attributes, and economic attributes[2]. Under the perspective of source attribution, data resources serve as the foundational inputs for the formation and capitalization of data assets[3]. Given the inherent difficulty in tracing the circulation and ownership chain of data resources, the verification of data provenance legitimacy constitutes an essential procedure in the accounting recognition process of data assets[4]. Nevertheless, for fully open public data, concerns regarding the legality or compliance of data sources are generally immaterial. For conditionally accessible and exploitable data, authorization is generally granted by governmental or other public institutions to enterprises for operation, or through the execution of licensing agreements, thereby ensuring the legitimacy of data provenance. From the perspective of legal attributes, this process represents an exploration of data asset property rights. Current theoretical approaches to data property rights can be broadly categorized into three paradigms: the Utility Theory, the Empowerment Theory, and the Structural Theory[5]. The "Pragmatic Approach" adheres to the fundamental tenets of pragmatism[6]. Its core argument posits that when data ownership cannot be appropriately interpreted within the current legal framework, it is advisable to temporarily bypass the ownership issue and instead focus on the expected outcomes of the property rights system design[7]. Accordingly, data rights should transcend the traditional conception of property rights and emphasize the interactive relationships of interests among participants in the data factor market.The "Empowerment Approach," by contrast, argues that existing categories of property rights are not directly applicable to data[8]. It therefore advocates the establishment of new proprietary rights or the granting of limited exclusivity to data. The "Structural Theory" posits that data rights possess a complex property-rights structure, thereby necessitating the construction of models such as a "bundle of rights." From an economic attributes perspective, the notion that data embody value has been widely acknowledged[9]. Considering the circulation of data as a production factor, data assets can be categorized into "resource-based data assets" and "operational data assets." The former refers to data assets that have potential development value but have not yet entered market circulation and generally lack specific application scenarios, whereas the latter refers to data assets that have been productized and are tradable in the market[10].

The accounting recognition of public data assets can be explored with reference to the relevant accounting standards, according to the classification and ownership of data asset items. Current research on the attribution of data assets mainly presents four perspectives[11]. The first view holds that data assets share similar characteristics with other productive assets, as they are generated in the course of production and can be repeatedly utilized over the long term to generate economic benefits for entities; therefore, they may be accounted for as fixed assets[12]. However, this perspective overlooks the non-depletive and replicable nature of public data assets. Public data assets can be utilized an unlimited number of times and may even appreciate in value through repeated use, which marks a substantial distinction in their economic substance.A second view contends that data assets are held for sale or for consumption in the course of future operations, and therefore can be accounted for as inventories[13]. Nevertheless, the low frequency of data asset sales and transactions does not constitute ordinary activities of the entity, thus creating a conceptual inconsistency with the definition of inventories under accounting standards. Third, some scholars argue that data assets possess the identifiable and non-physical characteristics of intangible assets and therefore should be recognized as such. However, while intangible assets typically emphasize exclusive control and legal enforceability, the value of data assets lies in their capacity for sharing and circulation[14]. This divergence in attributes leads to inconsistencies in the accounting recognition and measurement logic.

Research on the measurement of public data assets remains limited; however, it can draw on the existing approaches to accounting measurement of data assets. Current studies on data asset measurement present relatively fragmented perspectives, which can be summarized as follows.First, the valuation of data assets is highly context-dependent, as their value varies significantly across application scenarios. Accordingly, the transaction price of a data asset can be regarded as a reflection of its value in a single exchange[15].Second, both the market approach and the income approach are subject to stringent applicability conditions, making the cost approach a more prudent method for accounting measurement of data assets.Third, fair value is currently considered the most reliable representation of the actual value of data assets[16]. Nevertheless, given the inherent difficulty in determining their useful life, subsequent measurement should not involve amortization. In adherence to the principle of prudence, entities should perform an annual impairment test for data assets at the end of each fiscal year.Fourth, a combined application of the cost approach and fair value measurement is recommended to provide a more comprehensive representation of data asset value[17].

In summary, existing studies have explored data asset accounting from multiple dimensions, yet there remain notable divergences regarding the accounting recognition and measurement of data resources. Research specifically focusing on the accounting treatment of public data assets remains limited. This paper begins by examining the connotation of public data, further clarifying the concept of public data assets and their accounting recognition criteria. It then analyzes the accounting measurement and bookkeeping treatments involved in the acquisition, amortization, subsequent expenditures, impairment, and disposal of public data assets within administrative and public institutions. The objective is to effectively reflect the value and management of public data assets, thereby providing robust accounting support for decision-making in public sector entities.

3 PUBLIC DATA ASSETS

3.1 Public Data

Public data initially manifests as government data and administrative data, reflecting the primary attributes of public institutions and the nature of their administrative functions. With the deepening advancement of China's data circulation strategy, the concept of public data has expanded beyond the traditional understanding of "publicly owned" data to encompass "data possessing public value." Data from enterprises, institutions, and social organizations is gradually being incorporated into the scope of public data openness regulations. However, a unified definition of "public data" has yet to be established. Currently, the definition of public data primarily encompasses three dimensions.First, some regulations define it based on its inherent characteristics. For instance, the Beijing Municipal Measures for the Administration of Public Data define public data as "various types of data recorded and stored through computer information systems that possess public utility value and do not involve state secrets, trade secrets, or personal privacy."Second, other frameworks delineate public data by ownership and source of generation. The Provisional

Measures of Zhejiang Province for the Opening and Security Management of Public Data define public data as "data resources obtained by administrative authorities at all levels and public institutions with administrative or service functions in the lawful performance of their duties."Third, certain jurisdictions further refine the scope of data-holding entities. The Implementation Rules of Shanghai Municipality on Public Data Opening explicitly include "organizations providing public utilities such as water supply, electricity, gas, and public transportation." Based on a comprehensive review of current regional policies and accounting standards, and in alignment with the evolving policy trend of data factor circulation in China, this study defines public data as various categories of data resources collected or generated by administrative and public institutions in the course of performing public governance functions or delivering public services.

3.2 Public Data Assets

According to Document Caihui [2023] No. 11 issued by the Ministry of Finance, Notice on the Issuance of the Provisional Regulations on Accounting Treatment Related to Corporate Data Resources (hereinafter referred to as the "Provisional Regulations"), enterprises are required to conduct relevant accounting treatment for "data resources that are recognized as intangible assets, inventories, or other asset categories in accordance with the Accounting Standards for Business Enterprises (ASBEs), as well as data resources that are legally owned or controlled by the enterprise and are expected to bring future economic benefits but are not recognized as assets because they fail to meet the recognition criteria stipulated in the ASBEs."Therefore, the recognition of data resources as data assets must satisfy the definition of an asset under the Basic Standard of the Accounting Standards for Business Enterprises, along with two specific conditions: (1) it is probable that future economic benefits associated with the resource will flow to the enterprise; and (2) the cost or value of the resource can be measured reliably.Data assets that meet this definition are limited to data products and source datasets embedded in data products. The term data products refers to product forms that are designed for specific application scenarios and require embedded data to provide services. During the processes of data acquisition, data asset management, and data asset operation, such data products are generated through the processing of computing power and algorithms, forming data outputs that deliver services to end users.

The key to defining public data assets lies in how the term "public" is conceptualized. Within the composition of data products, the embedded data sources are inherently diverse, encompassing public data, social data, or a combination thereof, and in some cases consisting solely of one type. However, whether a data product falls within the "public" domain cannot be determined solely based on the nature of the embedded data. Instead, the decisive criterion should be the ownership attribution of the data product.Specifically, when a data product is independently developed by a public sector entity or developed by a third party under commission but with ownership vested in the public sector entity, it should be recognized as a public data product, irrespective of whether the underlying data possess "public" attributes. Accordingly, public data products refer to those data products that are developed or commissioned by administrative or public institutions, using fiscal funds or under government-granted concessions, in the course of performing public management functions or delivering public services. Public data products not only generate inflows of economic benefits for specific entities but also possess substantial potential for administrative and service functions, thereby creating political, social, and other multidimensional values. According to the Ministry of Finance Document No. 141 [2023], Guidelines on Strengthening Data Asset Management, the definition of public data assets extends beyond the criterion of "generating economic benefits" to include "the potential to produce administrative and service functions."Public data assets represent the assetized form of public data, encompassing public data products, public datasets embedded within such products, as well as public datasets incorporated into other data products. Accordingly, this study defines public data assets as data resources formed by administrative or public institutions in the course of performing statutory duties or delivering public services, which are held or controlled by specific entities and are expected to generate either administrative and service potential or inflows of economic benefits.

3.3 Characteristics of Public Data Assets

Public data assets differ fundamentally from traditional assets, exhibiting distinct characteristics such as non-rivalry, non-excludability, temporality, non-depletability, and value indeterminacy. Non-rivalry implies that a given public data asset can be simultaneously utilized by multiple users without diminishing its usability or economic utility. Non-excludability indicates that the utilization of such assets does not preclude other potential users, thereby reflecting their inherent public accessibility and shared nature. Temporality refers to the extent to which public data assets accurately and promptly reflect real-world phenomena or events. Non-depletability denotes that the use of public data assets does not entail physical deterioration or economic depletion arising from their consumption. Value indeterminacy signifies that the value of public data assets is not static; it may appreciate as application scenarios expand and data analytics technologies advance, or depreciate rapidly due to data obsolescence, technological innovation, or shifts in market demand—potentially resulting in complete loss of value.

In addition, public data assets exhibit distinct characteristics.First, public data assets are inherently multi-sourced, involving participation from diverse stakeholders, where openness and exclusivity coexist. During the processes of data collection, processing, and utilization, multiple entities—such as government and public institutions, social organizations, corporate bodies, and individuals—contribute to their formation. In some cases, these assets may even originate from confiscations, donations, or other non-market transactions.Second, public data assets embody both scarcity and authority. Although they are characterized by large volume and extensive coverage, each professional domain contains unique and domain-specific datasets. The difficulty of acquisition, high processing costs, and restricted applicability in certain use contexts lead to relative scarcity and heightened value in specialized data categories. Public data assets are typically acquired by governmental and public institutions in accordance with legal and regulatory requirements, ensuring both compliance and validity. The management of public data assets adheres to standardized governance frameworks, under which data ownership, processing, and operation are implemented by specialized agencies. Such structured and regulated procedures ensure the authority and reliability of data, thereby enhancing the credibility and recognition of public data assets.Third, public data assets exhibit a high degree of sensitivity. They encompass information across diverse dimensions of social production and everyday life, including personal privacy data, corporate trade secrets, and information involving public or national interests. As a result, public data assets are characterized by substantial sensitivity and require stringent controls over access and disclosure.Fourth, public data assets embody multi-dimensional and integrated value attributes. Their utilization and development should reflect both economic and social benefits. At the macro level, public data assets support national reform and development strategies, facilitating the modernization and digital transformation of government governance. At the meso level, public data provides decision-making references for relevant authorities in formulating industrial policies and implementing sectoral regulation, contributing to structural adjustment and optimized resource allocation. At the micro level, public data serves as an operational resource for enterprises, guiding market expansion, managerial decision-making, and internal governance, thereby promoting sustainable corporate development.

4 ACCOUNTING RECOGNITION OF PUBLIC DATA ASSETS IN ADMINISTRATIVE AND PUBLIC INSTITUTIONS

4.1 Accounting Recognition Criteria for Public Data Assets of Administrative and Public Institutions

4.1.1 Public data assets have clear sources

Public data assets originate from past transactions or events that occur in the process of administrative and public institutions performing their statutory duties or delivering public services. Specifically, public data are obtained by these institutions, through legally prescribed procedures, from designated entities in the course of fulfilling their functions. Such data primarily fall into the following five categories. The first category comprises governmental data, referring to information collected or obtained by public authorities in the lawful performance of their administrative duties.The second category includes data generated, collected, and held by public service and administrative entities, such as state-owned enterprises or public institutions, in the course of delivering their mandated functions.The third category pertains to data gathered or acquired by specialized institutions financed by public funds, which operate in areas involving public interest and thus possess inherent public value.The fourth category covers data owned by social organizations with public management or service attributes, where the information is closely related to major public interests.The fifth category encompasses other types of data associated with public service domains.All of the above categories generally originate from past transactions or events supported by verifiable documentation, ensuring the traceability, reliability, and authenticity of public data sources.

From the perspective of public data supply, administrative and public institutions, as the primary entities responsible for data collection, undertake critical duties in the provision of data. They are accountable for the hierarchical classification and governance of data generated and collected in the course of fulfilling their administrative functions, thereby ensuring the accuracy and integrity of such data. Specifically, Big Data Centers act as data aggregators, integrating massive volumes of public data resources within a given region or sector to construct comprehensive data resource maps. Meanwhile, data regulatory authorities are responsible for coordinating the unified construction of regional public data catalogues, formulating the public data directory, and ensuring the compliant utilization and effective management of public data resources.From the perspective of data circulation, data operating entities conduct authorized data operations in accordance with the relevant procedures and provisions stipulated in the Administrative Measures for the Authorized Operation of Public Data. In practice, they adhere to the principle of “data availability without visibility,” ensuring that raw data remain within jurisdictional boundaries while being made usable for authorized applications. These entities further engage in the development of public data products under such regulatory constraints. During the circulation process, data regulatory authorities, Big Data Centers, and data source institutions are responsible for supervisory and compliance functions, including the qualification review of operating entities, approval of data utilization, oversight of data development and application, as well as the supervision of market exit mechanisms for operators. Collectively, these governance measures provide a framework for compliance disclosure and full-process supervision, thereby supporting the assetization and accounting recognition of public data resources.

4.1.2 Held or controlled by a specific entity

The ownership of public data assets, held or controlled by specific entities, is a matter of discussion. Public data assets differ significantly from traditional assets, exhibiting characteristics such as non-rivalry, non-exclusivity, time-sensitivity, and non-depletion. Traditional property rights concepts are difficult to fully apply. Public data assets exhibit greater multi-sourced origins, with rights trends becoming increasingly relative and diversified. A single statutory ownership framework struggles to comprehensively regulate data ownership relationships. The Central Committee of the Communist Party of China and the State Council issued the "Opinions on Establishing a Basic Data System to Better Leverage the Role of Data as an Economic Factor," exploring a data property rights framework based on the "three-rights separation" model: data resource holding rights, data processing and usage rights, and data product operation rights. Data resource ownership refers to the rights held by relevant entities to manage, utilize, derive benefits from, and dispose of data resources within the scope prescribed by laws, regulations, or contracts. It constitutes a form of relative possession, distinguished by the ability of multiple entities to simultaneously hold such rights without interfering with each other's use of the data. Data processing and utilization rights refer to the entitlement of relevant entities to employ various methods and technical means to collect, utilize, analyze, and process data, subject to compliance with applicable laws, regulations, or contractual agreements. By exercising these rights, entities can conduct in-depth mining and processing of raw data, transforming it into more valuable information formats tailored to specific needs, thereby further unlocking the latent potential of data. Data product management rights refer to the rights of relevant entities to possess, use, derive benefits from, and dispose of data products within the constraints of relevant laws, regulations, or contracts. Through these rights, entities can bring processed data products to market, engage in commercial operations, and realize data value. For public data assets, administrative institutions and other organizations, as the collectors and controllers of public data resources, possess relatively clear "ownership" rights over such resources, making it easier to meet asset recognition standards. However, the exercise of "usage rights" and "operating rights" for public data assets is more complex. When processing, utilizing, or publishing public data, data operators should establish contractual mechanisms through negotiations with administrative institutions. These agreements should include background and qualification reviews of authorized entities to verify their operational history, data security credentials, operational risks, and foreign investment risks. Additionally, the agreements must explicitly state that data processing activities are conducted under the unified arrangements of administrative institutions, thereby constraining the authorized entity's identity, the scope of data, and the purpose of data processing. Such agreements should also clearly define the protection obligations of all parties involved in public data processing activities. Public data assets must be supervised and managed in accordance with relevant laws and regulations, such as the Data Security Law, to safeguard public interests. However, public data involving national security-sensitive areas, while potentially qualifying as public data assets under certain conditions, cannot be disclosed and ultimately cannot be included in the balance sheet.

From a practical perspective, public data assets in administrative and public institutions primarily involve the following four types of entities. First, industry regulatory authorities and supervisory agencies. Local government public data regulatory bodies are generally big data authorities, such as Big Data Bureaus or Government Data Bureaus, though in some regions they may fall under departments like Industry and Information Technology, Economic and Information Technology, or Cyberspace Administration. With the establishment of the National Data Administration, public data management responsibilities will gradually be consolidated under local big data authorities. Second, public functional departments and institutions. These data source entities, including public functional departments and relevant public institutions, are responsible for providing public data resources in accordance with laws and regulations. They bear accountability for the quality and security of the public data they supply. Third, authorized operating entities. As publicly-owned means of production belonging to the entire population, public data is managed by government departments. The preferred approach involves entrusting public data to public institutions or local state-owned enterprises for market-oriented operations. Authorized entities undertake the development, maintenance, and daily management of public data operation service platforms, engage in demand communication with data users, and facilitate the provision of data products and services. Fourth, public data users. Users must adhere to the scope of data usage stipulated in agreements or contracts, and are prohibited from transferring acquired data to third parties, whether for compensation or gratuitously. They assume obligations to safeguard public data security and must accept the tracking, evaluation, and supervision of their public data utilization activities by government departments and public data providers.

4.1.3 Costs or values can be reliably measured

For administrative and institutional units, determining the cost or value of public data assets must be based on verifiable evidence. Throughout the processes of data collection, management, storage, and development, detailed records of labor, material, and financial inputs are typically maintained and supported by vouchers such as invoices, contracts, and payroll records. In some instances, however, it is necessary to make a reasonable estimate of the cost or value of public data assets based on the most current information available.From an accounting perspective, the measurement of cost or value for public data assets held by administrative units can draw on traditional asset valuation methodologies, primarily encompassing the income approach, market approach, and cost approach. The core logic of the income approach is to estimate a reasonable value by discounting the expected economic benefits derived from potential future applications of the public data assets. Theoretically, this method is suitable for public data assets with well-defined usage scenarios and quantifiable future economic benefits. However, public data assets often exhibit multi-dimensional value integration, with social effects that are difficult to quantify, and their value may be subject to significant uncertainty, limiting the applicability of this approach.The market approach estimates the value of target public data assets by referencing recent transaction prices of comparable or similar public data assets in the open market. When a sufficiently rich variety of public data transaction types and models exists, enabling the collection of relevant comparable indicators, the market approach can be more appropriate. Nevertheless, the value of public data assets is highly dependent on specific application scenarios, and their characteristics—such as sensitivity and non-competitiveness—make it challenging to find truly comparable or similar public data assets in the market. The cost approach primarily refers to measuring the value of public data assets by aggregating the various costs incurred throughout the data production process, including acquisition costs, processing costs, operational and maintenance costs, administrative costs, and security-related costs. At present, valuation techniques for public data assets based on the cost approach have matured. The consumption of hardware, software, and human resources during standardized processes—such as data collection, storage, cleaning, and anonymization—can be accounted for with relative clarity. Since these processes typically do not involve customized development tailored to specific applications, the potential for extracting additional value from public data resources is limited, thereby ensuring high measurement accuracy. From a prudence perspective, adopting the cost approach as the measurement basis is generally reasonable for most public data assets.

4.1.4 Expected to generate management service potential or bring in economic benefits

Circular No. 141 [2023] of the Ministry of Finance, "Notice on Issuing the Guiding Opinions on Strengthening Data Asset Management," expands the definition of public data assets. Beyond "generating economic benefits," it adds "possessing the potential to deliver management services." The value of public data assets extends beyond economic returns, broadly manifesting in their capacity to propel social progress and enhance the service efficacy of modernized government governance. This encompasses multifaceted value attributes spanning political, social, and other dimensions. Economically, public data assets leverage open sharing and market-oriented operations to provide continuous "data momentum" for the digital economy. This drives industrial development, generates direct economic benefits for specific entities, and optimizes internal operational processes—enhancing efficiency and reducing costs—thereby creating indirect economic value. From a social perspective, developing and utilizing public data assets helps drive social innovation, spawning new knowledge and products that enhance the quality of public services, improve people's well-being, and realize social value. Furthermore, public data assets play a crucial role in advancing the modernization of government governance, enhancing the scientific basis of decision-making, and boosting government credibility. As the construction of digital government continues to advance, its political value is becoming increasingly prominent. Whether public data can realize its management and service potential or generate economic returns depends on different value realization scenarios, primarily including: First, application scenarios that directly generate economic returns through market-oriented operations and authorized usage; Second, application scenarios that indirectly create economic value by improving administrative efficiency and reducing operational costs; Third, social value scenarios that empower enterprises and the public through open sharing, optimize public service processes, and enhance service quality; Fourth, political value scenarios that elevate government governance standards and decision-making scientificity.

4.2 Scope of Ownership for Public Data Assets of Administrative and Public Institutions

Regarding the attribution of public data assets, their classification can be explored by referencing relevant accounting standards based on the nature of the data asset. The Interim Provisions treat data resources used internally by enterprises as inventories, while data resources intended for external transactions are recognized as intangible assets. Inventory refers to finished goods or merchandise held for sale in the ordinary course of business, products in the process of production, and materials consumed during production or the provision of services.First, inventory originates from routine business activities and possesses high liquidity and realizable value. Public data assets, however, are infrequently sold or exchanged and therefore do not qualify as part of an entity’s ordinary operating activities. Second, the purpose of holding inventory by a specific entity is for consumption or sale in the ordinary course of business. Whether an asset qualifies as inventory depends primarily on its intended use in routine operations. If an asset is held not for consumption or sale in ordinary activities, even if it exhibits inventory-like characteristics, it does not meet the definition of inventory and cannot be accounted for as such. Public data assets are, by nature, processed and structured data derived from massive information sources, providing targeted analytical value and reflecting political, economic, and social significance. They are not directly consumed or sold, and thus do not satisfy the definition of inventory or accurately reflect the status of public data assets held by administrative and institutional units.Intangible assets refer to identifiable non-monetary assets without physical substance that an entity controls or owns. They typically embody rights, patents, or comprehensive capabilities that enhance service potential, but lack physical form. Public data assets, however, are generated through collection, organization, and analysis processes and can be shared, transmitted, or transacted. Their storage requires information system media, and their characteristics—including non-competitiveness, non-exclusivity, shareability, and non-consumptiveness—render them incompatible with the existing intangible asset accounting framework.Accordingly, it is recommended that administrative and institutional units establish a separate accounting subject for “Public Data Assets,” enabling independent recognition and measurement of the public data assets held, and reporting them separately on the balance sheet.

5 ACCOUNTING MEASUREMENT OF PUBLIC DATA ASSETS IN ADMINISTRATIVE AND PUBLIC INSTITUTIONS

In the economic transaction processing of administrative and institutional units, the Government Accounting System provides a clear framework and guidance for accounting practice, characterized by the distinctive features of “dual functions, dual bases, dual elements, and dual reporting.” Specifically, it implements both budgetary accounting and financial accounting functions, applies the cash basis for budgetary accounting and the accrual basis for financial accounting, recognizes dual accounting elements for both budgetary and financial accounts, and requires the preparation of both final budget reports and financial statements at the end of the period.Budgetary accounting focuses on the management of budgetary fund inflows and outflows, reflecting budget execution and providing a basis for budget formulation and adjustment. Financial reporting, in contrast, emphasizes the presentation of an entity's financial position and operational performance, supporting financial decision-making and management. Under a comprehensive budget management framework, the accounting system of administrative and institutional units not only records financial information regarding economic events but also processes budgetary information. Together, financial and budgetary information constitute the accounting measurement basis for public data assets, ensuring the completeness and consistency of accounting information. This dual accounting system enables administrative and institutional units to monitor budget execution more effectively, optimize resource allocation, enhance operational efficiency, and provide reliable financial evidence for both external oversight and internal decision-making.

5.1 Accounting Measurement Model for Public Data Assets in Administrative and Public Institutions

Currently, the measurement of data assets primarily considers three valuation models: fair value, present value, and historical cost. The fair value measurement model is capable of reflecting the true economic value of public data assets, exhibits strong timeliness, and aligns closely with the intended usage scenarios of these assets. However, in China, both the activity level and transparency of the data trading market remain limited, making it difficult to identify identical or comparable transactions for public data assets in an open market. Consequently, fair value is currently not suitable for measuring public data assets held by administrative and institutional units.The present value approach estimates the value of an asset by discounting its expected future cash flows at an appropriate discount rate, which can capture the prospective economic benefits of public data assets. Nevertheless, this method is subject to significant subjectivity and potential measurement inaccuracies, raising the risk of overstatement in the valuation of public data assets.Moreover, public data assets possess unique characteristics, and the future value they generate under current conditions is inherently difficult to quantify reliably in monetary terms, which further complicates precise measurement.

Historical cost represents the total expenditure incurred by an accounting entity to acquire or create an asset. Measurement at historical cost provides an objective and faithful representation of the acquisition cost of public data. For administrative and institutional units, whether public data assets are internally developed or externally purchased, the associated costs can be reliably determined, minimizing biases arising from subjective judgment. These units are also actively exploring the establishment of a public data cost accounting system, which comprehensively considers factors such as data collection, storage, processing, and management, and applies a classified cost accounting approach. Under the guidance of sectoral authorities, pricing regulators, and fiscal departments, and with reference to relevant charging standards and procedures, regional standards for public data usage fees are formulated. Therefore, under current data market conditions and considering practical operability, historical cost measurement can be applied to public data assets, supporting the principle of prudence and ensuring the reliability of accounting information.

Furthermore, when the cost of public data assets cannot be reliably determined and their objective value cannot be reflected, the measurement of such assets may refer to the accounting approach applied to historical artifacts, namely a dual measurement method combining nominal amounts and physical units. The Government Accounting Standards – Basic Standards stipulate that "the measurement attributes of assets primarily include historical cost, replacement cost, present value, fair value, and nominal amount… where none of the above measurement attributes can be applied, assets shall be measured at nominal amount (i.e., RMB 1)." This provision provides an effective reference for administrative and institutional units in addressing the challenge of quantifying the value of public data assets upon acquisition.

5.2 Initial Measurement of Public Data Assets

The initial measurement of public data assets primarily concerns the acquisition of such assets. Administrative and institutional units acquire public data assets through several main channels, including self-development, purchase, donation, gratuitous transfer, and commissioning other entities for development.First, self-development. Public data resources must undergo multiple processes—collection, organization, processing, storage, management, and application—before they can constitute valuable public data assets. Therefore, expenditures incurred by administrative and institutional units in self-developing public data assets should be distinguished between expense recognition and capitalization phases. Expenditures classified as expenses are recorded under the account "Public Data Development Expenditure" and are fully transferred to current period expenses at the end of the period. Expenditures classified as capitalizable costs are initially recorded under "Public Data Development Expenditure" and transferred to the "Public Data Assets" account upon reaching the intended usable state. If it is not possible to distinguish between expense and capitalization, but the public data asset has been legally obtained according to relevant procedures, the total expenditure is directly recognized under "Public Data Assets."Second, purchase, donation, or gratuitous transfer. Public data assets acquired through purchase, donation, or gratuitous transfer are recognized at their determined cost and recorded under "Public Data Assets." If the donation is recognized at a nominal value, the asset is recorded at the nominal amount.Third, commissioned development by other entities. Public data assets commissioned to third parties for development are treated similarly to purchased assets. However, if the contract stipulates advance payments for development, the advance is recorded under "Prepaid Expenses." Upon completion and delivery of the developed public data asset, and payment of the remaining or total development fees, the total development cost is recognized under "Public Data Assets."Specific accounting treatments are summarized in Table 1.

Table 1 Accounting Treatment for Acquisition of Public Data Assets

Business and Matters		Financial Accounting	Budget Accounting
In-house development	Expenses for self-developed projects	Debit:Public Data Development Expenditures Credit: Employee Compensation Payable / Government Grant Income, etc. Debit: Operating Expenses / Administrative Expenses, etc. Credit: Public Data Development Expenditures	Debit:Operating Expenses/Business Expenses, etc. Credit: Budgeted Revenue from Government Appropriations/Fund Balances
	Capitalized expenditures for self-developed projects	Debit: Public Data Development Expenditures Credit: Employee Compensation Payable / Government Grant Revenue, etc.	Debit: Operating Expenses/Business Expenses, etc. Credit: Budgeted Revenue from Government Appropriations/Fund Balances
	Development completed, achieving the intended purpose and forming a public data asset.	Debit: Public Data Assets Credit: Public Data Development Expenditures	No accounting entries
	Unable to distinguish between expenses and capital expenditures, but public data assets have been acquired in accordance with relevant legal procedures. .	Debit: Public Data Assets Credit: Fiscal Appropriations Received / Bank Deposits, etc.	Debit: Operating Expenses/Business Expenses, etc. Credit: Budgeted Revenue from Government Appropriations/Fund Balances
Purchased externally	Costs determined by external procurement	Debit: Public Data Assets Credit: Fiscal Appropriations Receivable/Accounts Payable/Bank Deposits, etc.	Debit: Program Expenses/Operating Expenses/Administrative Expenses, etc. Credit: Budgetary Revenue from Government Appropriations/Fund Balances
Accepting donations	Costs determined upon acceptance of donations	Debit: Public Data Assets Credit: Bank Deposits, etc. Donation Income	Debit: Other Expenses Credit: Fund Balance
	Record at nominal value	Debit: Public Data Assets Credit: Donation Revenue Debit: Other Expenses Credit: Bank Deposits, etc.	Debit: Other Expenses Credit: Fund Balance
Transfer without compensation	Costs determined for non-reimbursable transfers	Debit: Public Data Assets Credit: Bank Deposits, etc. Net Assets Transferred Without Consideration	Debit: Other Expenses Credit: Fund Balance
Outsource development to other entities	Prepay development fees as stipulated in the contract	Debit: Prepaid Accounts Credit: Government Grants Received / Cash on Hand, etc.	Debit: Program Expenses/Operating Expenses/Administrative Expenses, etc. Credit: Budgetary Revenue from Government Appropriations/Fund Balances
	Public Data Asset Delivery, Payment of Remaining or Full Development Fees	Debit: Public Data Assets Credit: Prepaid Accounts Government Grants Received / Bank Deposits, etc.	Based on the amount of remaining funds paid: Debit: Program Expenses/Operating Expenses/Administrative Expenses, etc. Credit: Budgetary Revenue from Government Appropriations/Fund Balances

5.3 Subsequent Measurement of Public Data Assets

5.3.1 Amortization

Public data assets typically generate benefits for administrative and public institutions over a period exceeding one year and may be classified as long-term assets. However, public data assets also exhibit significant time-sensitivity, with their value or rights potentially expiring or diminishing due to changes in intended use or external circumstances.

Therefore, administrative and public institutions should reasonably estimate the expected useful life of public data assets upon acquisition. Where the useful life cannot be foreseen, such assets should be treated as public data assets with an indefinite useful life. Administrative and public institutions shall amortize public data assets with a determinable useful life, allocating the cost to relevant expenses or current period costs based on their intended use. Public data assets with an indefinite useful life, those fully amortized but still in use, and those measured at nominal value shall not be amortized. No accounting entries shall be made in budget accounting. Specific accounting treatments are shown in Table 2.

Table 2 Accounting Treatment for Amortization of Public Data Assets

Business and Matters	Financial Accounting	Budget Accounting
Amortization of public data assets	Debit: Operating Expenses/Unit Administrative Expenses, etc. Credit: Accumulated Amortization of Public Data Assets	No accounting entries

5.3.2 Subsequent expenditures

Public data assets are characterized by non-consumability and replicability, and their value may appreciate during future use. When the value of public data assets increases significantly due to expanded application scenarios, technological advancement, or enhanced utilization efficiency, such appreciation should be recognized. Value appreciation can be realized by remeasuring the public data asset and adjusting its carrying amount. The increment may be recorded in the "Provision for Appreciation of Public Data Assets" account, while also assessing whether subsequent expenditures meet the recognition criteria for public data assets.Specifically, amortization of the public data asset is temporarily suspended. The carrying amount of the public data asset is recorded in the "Provision for Appreciation of Public Data Assets" account, and the amount already amortized is recorded in the "Accumulated Amortization of Public Data Assets" account. Subsequent expenditures that meet the recognition criteria for public data assets are recorded in the "Provision for Appreciation of Public Data Assets" account at the amount incurred. Upon completion of the appreciation process and delivery of the suspended-amortization public data asset for use, the balance in the "Provision for Appreciation of Public Data Assets" account is transferred to the "Public Data Assets" account.Expenditures that do not meet the recognition criteria for public data assets should be expensed and recorded under accounts such as "Operating Expenses" or "Administrative Expenses." The detailed accounting treatment is presented in Table 3.

Table 3 Accounting Treatment for Subsequent Expenditures on Public Data Assets

Business and Matters	Financial Accounting	Budget Accounting
Subsequent expenditures meeting the criteria for public data asset recognition	Debit: Public Data Appreciation Reserve Public Data Accumulated Amortization Credit: Public Data Assets Debit: Public Data Appreciation Reserve Credit: Government Grants Received/Bank Deposits, etc.	Debit: Program Expenses/Operating Expenses/Administrative Expenses, etc. Credit: Budgetary Revenue from Government Appropriations/Fund Balances
Achieve value-added transformation to fulfill intended purposes and establish public data assets.	Debit: Public Data Assets Credit: Public Data Appreciation Reserve	No accounting entries
Subsequent expenditures that do not meet the criteria for public data asset recognition	Debit: Operating Expenses/Unit Administrative Expenses, etc. Credit: Government Grants Received/Bank Deposits, etc.	Debit: Program Expenses/Operating Expenses/Administrative Expenses, etc. Credit: Budgetary Revenue from Government Appropriations/Fund Balances

5.3.3 Impairment

The Government Accounting Standards—Basic Standards stipulate that to accurately reflect the financial position of government entities, public institutions must conduct a comprehensive review of accounts receivable and other receivables not required to be remitted to the treasury at the end of each year, in accordance with the principle of prudence. They must assess the likelihood of recovery and recognize bad debt losses by accruing provisions for anticipated bad debt losses. Other assets are not required to be impaired temporarily. Therefore, public data assets should not be subject to impairment provisions. However, the value of public data assets is highly correlated with usage scenarios, timing, and other factors, making them susceptible to value fluctuations influenced by internal and external environmental factors affecting users. If annual impairment testing cannot be conducted, administrative and public institutions should perform a value assessment of public data assets at the end of each year and disclose the results of such assessments in their financial reports. This ensures users of financial reports have a full understanding of the financial status of public data assets.

5.3.4 Disposal

The disposal of public data assets by administrative and institutional units primarily includes methods such as sale, transfer, external donation, gratuitous allocation, and write-off upon approval. According to regulations, approved disposals of public data assets are recorded at the carrying amount of the disposed assets and recognized in the "Gains or Losses on Asset Disposal" account. For assets that have been amortized, the remaining balance is credited to the "Public Data Assets" account. Any expenses incurred during the disposal process are recorded in accounts such as "Cash and Cash Equivalents."In cases where an administrative or institutional unit transfers public data assets upon approval, and the transfer involves copies of public data products while the unit retains the underlying rights to use the public data resources, the cost of the disposed public data asset is allocated proportionally based on the transfer revenue relative to the total expected economic benefits generated by the asset. The specific accounting treatment is summarized in Table 4.

Table 4 Accounting Treatment for Public Data Asset Disposal

Business and Matters	Financial Accounting	Budget Accounting
Sale, Transfer	Debit: Asset Disposal Expense Accumulated Amortization of Public Data Assets Credit: Public Data Assets	No accounting entries
	Debit: Bank deposits, etc. Credit: Bank deposits, etc. Fiscal payments payable/Other income	If transfer income is included in the unit's budget as required: Debit: Fund Balances Credit: Other Budget Revenue
Overseas Donations	Debit: Asset Disposal Expense Accumulated Amortization of Public Data Assets Credit: Public Data Assets Bank Deposits, etc.	Debit: Other Expenses Credit: Fund Balance
Transfer without compensation	Debit: Transfer of Net Assets (Non-Compensated) Accumulated Amortization of Public Data Assets Credit: Public Data Assets Debit: Asset Disposal Expense Credit: Bank Deposits, etc.	Debit: Other Expenses Credit: Fund Balance
Approved for write-off	Debit: Asset Disposal Expense Accumulated Amortization of Public Data Assets Credit: Public Data Assets	No accounting entries

6 CONCLUSION

The development of public data resources is a critical measure to advance the market-oriented allocation of data as a production factor, a strategic initiative to unlock the potential of data assets, and a key pillar supporting the growth of the digital economy. This paper focuses on the accounting recognition and measurement of public data assets held by administrative and institutional units, systematically exploring the challenges arising from the unique characteristics of public data assets and the insufficient adaptability of the current accounting framework.The study clarifies the conceptual distinction between public data and public data assets, and delves into the recognition criteria for public data assets within administrative and institutional units, demonstrating both the feasibility and the particularities of recognizing such assets under existing accounting standards. Regarding measurement, through a comparative analysis of the applicability of inventory, intangible assets, and other relevant accounts under the current Government Accounting Standards – Specific Standards, the paper argues for establishing a dedicated primary account titled "Public Data Assets." Furthermore, it provides a detailed discussion on accounting treatment for public data assets across subsequent measurement stages, including initial recognition and amortization, subsequent expenditures, impairment assessment, and disposal, outlining practical approaches for each stage in accordance with professional accounting principles.

This article not only enriches the accounting framework for emerging assets within the field of government accounting, providing an accounting-based solution for the standardized management of public data assets, but also offers practical guidance for administrative and institutional units to enhance the efficiency of public data asset management and facilitate the market-oriented circulation of data as an economic resource. Future research could further explore dynamic valuation models for public data assets, as well as detailed accounting approaches that reflect differences across hierarchical levels and types of administrative and institutional units, thereby better accommodating the complexity and diversity inherent in data assets.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

FUNDING

This study was supported by: (1) Key Project of Humanities and Social Sciences in Scientific Research at Universities in Anhui Province in 2024: Research on Value Assessment of Government Public Data Resources (Project No.: 2024AH053399); (2) Key Project of Humanities and Social Sciences Scientific Research in Colleges and Universities of Anhui Province in 2024: Research on Accounting Issues of Public Data Assets under the Guidance of New Quality Productivity (Project No.:2024AH053402); (3) General Project of Philosophy and Social Sciences at Tongling University in 2023: Research on Pricing of Government Public Data Resources:Boundary Logic, Formation Mechanism, and Measurement Model (Project No.:2023tlxy18).

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