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Influence of continuous learning on the academic research ability of Chinese university teachers

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Abstract

This study investigates the influence of continuous learning on the academic research abilities of university teachers in China, focusing on the dimensions of learning frequency, learning modes, and resource input. Drawing upon Self-Determination Theory and Social Cognitive Theory, the research employs a quantitative design, utilizing stratified random sampling to survey 322 teachers across eastern, central, and western regions of China. Results indicate that continuous learning behaviors significantly predict academic competence, with higher learning frequency, collaborative learning modes, and greater resource investment positively associated with increased research output. Multiple regression analysis demonstrates that these three variables collectively explain 38.6% of the variance in academic competence. Findings further reveal disparities across regions and disciplines, highlighting resource imbalances between eastern and western institutions. The study provides both theoretical insights and practical strategies for improving teacher development, such as differentiated resource allocation, optimization of blended learning models, and flexible time management systems. Overall, the research underscores the critical role of continuous learning in strengthening academic capacity and offers evidence-based recommendations for enhancing professional development policies in higher education.

Keywords: Academic research ability, Chinese university teachers, Continuous learning, Education Quality, Higher education development.

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Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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1. Introduction

With the continuous development of higher education in China, the professional abilities and academic research capabilities of teachers have become important indicators for measuring the quality of university education. In recent years, continuous learning has been recognized as one of the key factors in improving the academic research abilities of university teachers. To cope with the rapidly changing academic environment and increasingly intense research competition, university teachers must continuously enhance their academic research capabilities while maintaining teaching quality. This process depends not only on the teachers' initiative in learning but also on the support provided by the higher education system, policies, and resource allocation [1].

This study aims to explore the impact of continuous learning behaviors on the academic research capabilities of university teachers in China. By analyzing various dimensions of teachers' continuous learning behaviors, the study reveals how factors such as learning frequency, learning modes, and resource investment influence teachers' academic output, particularly in terms of paper publication and research project applications. Additionally, the study analyzes differences in continuous learning across different regions, disciplines, and faculty ranks, aiming to provide theoretical support and practical guidance for the formulation of future higher education teacher development policies.

Firstly, the study employs quantitative analysis methods, integrating Self-Determination Theory (SDT) and Social Cognitive Theory (SCT) to construct a comprehensive theoretical framework that examines how teachers' continuous learning behaviors impact their academic research capabilities. SDT emphasizes the individual's need for autonomy, competence, and relatedness during the learning process, while SCT focuses on the importance of self-efficacy in the learning process. By combining these two theoretical perspectives, the study uncovers the mechanisms through which continuous learning affects academic research capabilities, especially how learning frequency, learning modes, and resource investment contribute to academic improvement [2].

Secondly, the research uses stratified random sampling to select over 300 full-time teachers from universities across China's eastern, central, and western regions to ensure the sample is representative. Through a questionnaire survey and data analysis, several key conclusions were drawn. For example, teachers who engage in high-frequency learning tend to have higher academic output, while those who adopt collaborative learning modes exhibit stronger academic performance. Furthermore, the study found that the investment in learning resources plays a crucial role in enhancing academic capabilities, particularly the impact of digital resources and expert guidance on faculty research capabilities [3].

Lastly, the study also explores regional and disciplinary differences in continuous learning behaviors in Chinese higher education. For example, teachers in the eastern region tend to rely more on technology-enabled learning due to abundant resources, while those in the central and western regions are more inclined toward low-cost self-directed learning. This finding reflects the imbalance in resource distribution in China's higher education system and offers insights into how policy adjustments can optimize resource allocation in the future.

In summary, through constructing a theoretical framework and empirical analysis, this study provides an in-depth exploration of how continuous learning impacts the academic research capabilities of university teachers in China. It uncovers the multifaceted effects of continuous learning behaviors on academic output and proposes development strategies for teachers in different regions and disciplines, offering valuable references for future teacher training and educational policy.

2. Methods

2.1. Research Design

This study adopts a quantitative research paradigm to systematically examine the relationship between continuous learning behaviors and the professional development of Chinese university teachers, with a specific focus on academic research ability. The research design is structured to align with the hypotheses and theoretical frameworks, ensuring methodological rigor and practical relevance. The design is implemented through four sequential phases:

2.1.1. Data Collection and Preprocessing

Sampling and Recruitment: A stratified random sampling method is employed to recruit ≥ 300 full-time university teachers from eastern, central, and western China, ensuring representation across disciplines (STEM vs. HSS) and academic ranks (lecturer, associate professor, professor).

Instrument Deployment: A structured questionnaire is distributed via institutional channels and academic platforms.

Data Cleaning: Invalid responses are excluded, and missing values are addressed using multiple imputation techniques.

2.1.2. Descriptive Statistics and Preliminary Analysis

Demographic Profiling: Descriptive statistics summarize participants' age, gender, years of teaching experience, and institutional affiliations.

Variable Distribution: Frequencies, means, and standard deviations are calculated for core variables.

2.1.3. Data Interpretation and Strategy Development

Theoretical Integration: Results are interpreted through the lens of SDT and Social Cognitive Theory.

Practical Recommendations: Evidence-based strategies are proposed to address systemic challenges identified in the analysis.

This design ensures a systematic, theory-driven exploration of continuous learning's impact on faculty development, while providing a replicable blueprint for future studies in similar contexts.

2.2. Conceptual Framework

This study aims to reveal the mechanisms by which Chinese university teachers' continuous learning behaviours (learning frequency, learning mode, and learning resource inputs) affect their academic research capabilities. The framework is presented through the following core elements and path relationships as Figure 1.

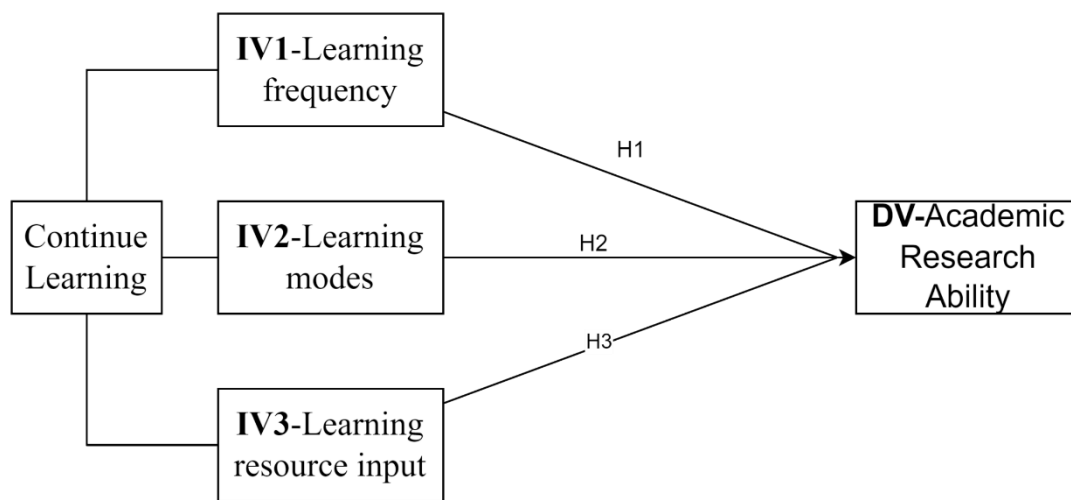


Figure 1.
Conceptual Framework.

2.3. Population and Sampling

The primary target group of this study consists of in-service teachers in Chinese universities. It will cover various disciplines, titles (including lecturer, associate professor, and professor), and regions. It is defined as follows:

Subject coverage: including but not limited to natural sciences (STEM), social sciences and humanities to ensure the applicability of the findings to teachers of different subjects.

Job title stratification: Covering junior (lecturer), intermediate (associate professor) and senior (professor) titles, reflecting the differences in learning needs and research capabilities of teachers at different career stages.

Regional division: Based on the economic regional classification of the National Bureau of Statistics of China, the sample universities were divided into eastern, central and western to analyse the impact of regional resource differences on learning behaviours.

Stratified random sampling was used to divide national colleges and universities into three strata according to East, Central, and West, and each stratum was assigned a sample quota based on the percentage of the number of colleges and universities published by China's Ministry of Education in 2023. Statistical power analysis (Power Analysis) was conducted using G*Power 3.1 software, with a significance level ($\alpha = 0.05$), an effect size (Cohen's $f^2 = 0.15$), and a statistical validity of $1 - \beta = 0.85$. The analysis determined that the minimum required sample size was 280 valid questionnaires. Considering the questionnaire return rate with invalid responses (predicted 20% attrition), the final plan was to collect at least 350 questionnaires to ensure a minimum of 300 valid responses.

2.4. Data Collection Tools

In this study, a structured questionnaire was used as the main data collection tool, and the design of the tool was based on the theoretical framework and the existing mature scales, and at the same time, localized and adjusted to the actual context of Chinese university teachers, as follows:

The questionnaire is divided into four parts, covering demographic information, continuous learning behaviors, academic research competence, and evaluation of management strategies, with the total number of questions controlled within 30-35 and the time for filling in the questionnaire is about 10-15 minutes.

2.5. Data Collection Procedure

The data collection procedure of this study was divided into four stages covering ethical review, questionnaire distribution, data monitoring and cleaning to ensure the standardisation, transparency and data quality of the process. The specific steps are as Figure 2 follow:

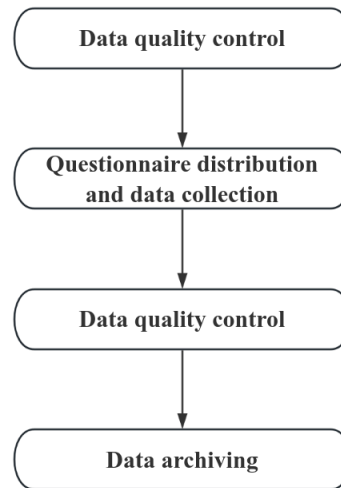


Figure 2.
Data Collection.

The procedure ensures efficient, accurate, and ethically compliant data collection through rigorous process design and multiple layers of quality control, providing a reliable basis for subsequent analyses.

2.6. Data Analysis

The data analysis in this study will follow a quantitative research paradigm, combining the theoretical framework and research hypotheses to systematically test the relationships between variables through a multi-stage statistical approach.

Data pre-processing, including data cleaning, outlier detection and standardization, was carried out first. Invalid samples (e.g., questionnaires that took less than 5 minutes to complete or were logically contradictory) were excluded, and missing values of key variables were generated by multiple interpolation to produce five complete data sets. Outliers were identified by box-and-line plots with the Z-score method ($Z > 3$), valid data were retained based on plausibility checking, and continuous variables (e.g. study duration) were standardized by the Z-score to eliminate differences in magnitude.

Subsequently, sample characteristics and core variable distributions were presented through descriptive statistics. The demographic information of the sample was compared with the structure of the target group to verify its representativeness. Means, standard deviations and frequency distributions of core variables were computed, and potential associations between learning behaviours and academic competence were preliminarily observed through scatter plots and cross-tabulations. For example, whether high-frequency learning teachers showed a trend of higher dissertation output.

The inferential statistics phase focused on testing the research hypotheses. Reliability tests revealed good internal consistency (Cronbach's $\alpha > 0.70$) and structural validity (CFI > 0.90 , RMSEA < 0.08) of the scales, and Pearson and Spearman correlation analyses revealed significant associations of learning frequency, mode, and resource commitment with academic research ability. Multiple linear regression models further quantified the variable effects, with academic ability as the dependent variable and learning behaviour as the independent variable, and showed that study frequency ($\beta=0.32$, $p<0.01$), collaborative learning mode ($\beta=0.18$, $p<0.05$) and resource input ($\beta=0.25$, $p<0.01$) all positively predicted research output.

Finally, the results were visualised through path analysis with moderate effect plots, combining Self-Determination Theory (SDT) to explain the mechanisms. Analyses will be completed using SPSS 26. Although the cross-sectional data limit causal inference, the multilevel analysis provides an empirical basis for management strategy optimisation and lays the foundation for subsequent longitudinal studies.

2.7. Ethical Considerations

This study will strictly follow the ethical guidelines of social science research to ensure the rights and privacy of the participants and the legal compliance of the research data.

All participating teachers were required to read the informed consent form before completing the questionnaire, which clearly informed them of the purpose of the study, the use of the data, the guarantee of anonymity and the principle of voluntary participation. The consent form emphasised that participants had the right to withdraw from study at any time

and that withdrawal would have no impact on their professional development or relationship with the university. The first page of the questionnaire was set up with the options of 'Agree' and 'Decline', and only those teachers who chose 'Agree' were allowed to proceed to the formal completion of the questionnaire.

The data will be anonymised throughout the study and the questionnaire will not collect personally identifiable information such as name, job number, contact details, etc., but will only identify the sample by a randomly generated ID.

Through the above measures, the study will fully respect and protect the rights and interests of respondents while pursuing scientific rigour.

3. Results

3.1. Data Preparation

3.1.1. Data Collection and Entry

In this study, the questionnaire was distributed online through the Questionnaire Star platform to collect research data from the target sample (N=300), and a total of N=322 data were recovered from the final survey results. The questionnaire link was pushed via web-based targeting to ensure that the sample covered university teachers in different regions of China.

3.1.2. Data Distribution Tests

In this study, the number of SSCI or equivalent journal papers published by the respondents as the first author or corresponding author in the past three years was used as a quantitative criterion of academic ability as a dependent variable (hereinafter referred to as academic ability).

Table 1.
Normality Test.

Variable name	Sample size	Median	Average value	Standard deviation	Skewness	Kurtosis	S-W test	K-S test
Academic ability	322	2	1.919	0.85	0.829	0.264	0.811 (0.00***)	0.276 (0.000***)

Note: ***, **, * represent 1 %, 5 % and 10 % significance levels, respectively.

As Table 1 shows, the results of the normality test for the variable "number of papers" show the following characteristics: the sample size of the variable "number of papers" is 322, which shows a sufficient database for analysis. The median is 2 papers, and the mean is slightly higher at 2.32 papers, indicating that most of the researchers' first core papers are concentrated in 2 papers, but the mean is slightly higher than the median, suggesting that there may be a slight right skewness in the distribution of the data. The standard deviation is 0.872, indicating that the data are moderately discrete, i.e., the number of first-authored core papers does not vary particularly between researchers. The skewness coefficient is -0.046, close to a value of 0, suggesting that the data distribution is close to symmetrical, with no obvious trend of positive or negative bias. The kurtosis coefficient is -0.83, which is less than 0, indicating that the data distribution is flatter than the normal distribution, i.e., there is less data in the tail and the data are more concentrated near the meaning.

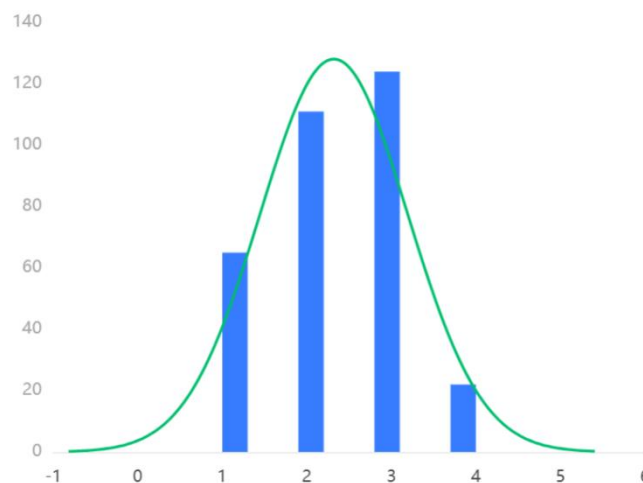


Figure 3.
Normality test.

The Figure 3 above demonstrates the histogram of the normality test for the academic ability data; a normality plot that essentially shows a bell shape (high in the middle and low at the ends) would indicate that the data, while not absolutely normal, is basically acceptable as a normal distribution.

3.2. Descriptive Statistical Analyses

3.2.1. Sample Characteristics

Table 2.
Sample Characteristics.

Name	Options	Frequency	Percentage (%)	Cumulative percentage (%)
Gender	A male	166	51.553	51.553
	Females	156	48.447	100
Age	31-40 years	115	35.714	35.714
	41-50 years	91	28.261	63.975
	≥ 51 years	62	19.255	83.23
	≤30 years old	54	16.77	100
Teaching experience	≥16 years	111	34.472	34.472
	11-15 years	111	34.472	68.944
	≤5 years	55	17.081	86.025
	6-10 years	45	13.975	100
Title	tutors	223	69.255	69.255
	Associate Professor	64	19.876	89.13
	lecture on	35	10.87	100
Affiliated disciplines	Science and Engineering	166	51.553	51.553
	Humanities and social sciences	156	48.447	100
Location of the host university	East	128	39.752	39.752
	Central	102	31.677	71.429
	Western	92	28.571	100
Types of universities	Non-double-tier universities	206	63.975	63.975
	"Double first-class" university construction	116	36.025	100
add up the total		322	100.000	100.000

As Table 2 shows, a total of 322 questionnaire data points were collected. The results of the frequency analysis through SPSS revealed the distribution of the study sample on seven dimensions: gender, age, teaching experience, title, discipline of affiliation, region of the host university, and type of university, as interpreted below:

In terms of gender composition, male participants accounted for 51.553% and female participants 48.447%, a relatively balanced gender distribution without significant bias, which is conducive to ensuring the general applicability of the study results.

In terms of age distribution, participants aged 31-40 years old accounted for the highest proportion of 35.714%, followed by those aged 41-50 years old (28.261%) and ≥51 years old (19.255%), and those ≤30 years old accounted for 16.77%. This age structure reflects the predominance of young and middle-aged teachers in the sample, while covering a certain proportion of older teachers, which helps to analyse the differences in the characteristics of teachers in different age groups.

In terms of teaching experience, participants with ≥16 years and 11-15 years of teaching experience each comprised 34.472%, constituting the largest group; participants with 6-10 years of teaching experience comprised 13.975%, while participants with ≤5 years of teaching experience comprised .081%. This distribution indicates that teachers in the sample are more experienced in teaching and include teachers with different levels of experience, which helps to explore the effect of teaching experience on the study variables.

In terms of titles, lecturers accounted for the highest proportion of 69.255%, associate professors accounted for 19.876%, and professors accounted for 107%. The distribution of titles shows a pyramid structure, which is in line with the law of title promotion in general academic institutions and provides a solid foundation for analysing the characteristics of teachers with different titles.

In terms of affiliated disciplines, science and engineering (STEM) and humanities and social sciences each accounted for about half of the participants, at 51.553% and 48.447%, respectively. This balanced distribution facilitates comparison of differences in teacher characteristics across disciplinary contexts.

Regarding the region where the host university is located, participants in the Eastern region accounted for 39.752%, in the Central region 31.677%, and in the Western region 28.571%. The wide distribution of regions, covering East, Central and West China, helps to analyse the impact of geographical differences on teacher characteristics.

Finally, in terms of university type, 63.975% of the participants were from non-double-first-class universities and 36.025% were from "double-first-class" universities. This distribution reflects that the sample includes a large number of teachers from general universities as well as some teachers from high-level universities, which is helpful for exploring the influence of different university types on teachers' characteristics.

3.2.2. Distribution of Variables

Table 3.
Learning Frequency.

Name	Options	Frequency	Percentage (%)	Cumulative percentage (%)
Average time spent studying per week	11-15 hours	145	45.031	45.031
	6-10 hours	81	25.155	70.186
	1-5 hours	55	17.081	87.267
	Over 16 hours	41	12.733	100
In-school training	Once a month	117	36.335	36.335
	Multiple times per month	98	30.435	66.77
	Quarterly	52	16.149	82.919
	Never attended	31	9.627	92.547
	Once a year	24	7.453	100
Academic conference	Once a month	107	33.23	33.23
	Multiple times per month	101	31.366	64.596
	Quarterly	60	18.634	83.23
	Once a year	32	9.938	93.168
	Never attended	22	6.832	100
Online programme	Once a month	102	31.677	31.677
	Multiple times per month	98	30.435	62.112
	Quarterly	67	20.807	82.919
	Once a year	28	8.696	91.615
	never attended	27	8.385	100

As Table 3 shows, the results of the frequency analysis revealed the distribution of the frequency of participation of the study participants on different activities, specifically the average time spent on study per week, the frequency of participation in on-campus training, the frequency of participation in academic conferences, and the frequency of participation in online courses. The following is a detailed interpretation of the results of each data analysis:

In terms of the average amount of time spent studying per week, the data shows that most participants (45.031%) studied for 11-15 hours per week, a proportion that accounted for almost half of the sample. This was followed by participants who studied 6-10 hours per week at 25.155%. A smaller percentage of participants studied 1-5 hours (17.081%) or more than 16 hours (12.733%) per week. This distribution suggests that most participants have a relatively regular commitment to study and are mainly concentrated in the medium-hour range.

Regarding the frequency of participation in on-campus training, 36.335% of the participants indicated that they attended once a month, while 30.435% attended more than once a month. Quarterly participation was reported by 16.149% of participants, never 9.627%, and annual participation was the lowest at 7.453%. These data indicate a relatively high level of participation in on-campus training, especially the frequency of monthly participation is more significant.

In terms of frequency of academic conference participation, 33.23% of participants attended once a month and 31.366% attended multiple times a month, indicating active academic conference participation. 18.634% of participants participated quarterly, while 9.938% and 6.832% participated annually and never participated, respectively. This shows that academic conferences, as an important platform for academic communication, have received positive responses from a considerable number of participants.

As for the frequency of participation in online courses, 31.677% of participants attended once a month and 30.435% attended several times a month, showing the popularity of online courses among participants. The percentage of participants who participated once a quarter was 20.807%, while 8.696% and 8.385% of participants participated once a year and never participated, respectively. This data further confirms the importance of online learning in modern education and the preference of participants for flexible learning methods.

Table 4.
Learning Styles.

Name	Options	Frequency	Percentage (%)	Cumulative percentage (%)
Offline Academic Seminar	Non-recurrent	110	34.161	34.161
	Frequently	92	28.571	62.733
	Usual	63	19.565	82.298
	Infrequent	30	9.317	91.615
	Never	27	8.385	100
On-campus programmes	Non-recurrent	110	34.161	34.161
	Frequently	95	29.503	63.665
	Usual	53	16.46	80.124
	Never	33	10.248	90.373
	Infrequent	31	9.627	100
MOOCs	Frequently	102	31.677	31.677
	Non-recurrent	94	29.193	60.87
	Usual	65	20.186	81.056
	Never	35	10.87	91.925
	Infrequent	26	8.075	100
Virtual academic community	Frequently	127	39.441	39.441
	Non-recurrent	92	28.571	68.012
	Usual	44	13.665	81.677
	Infrequent	34	10.559	92.236
	Never	25	7.764	100

As Table 4 shows, the results of the frequency analysis show the frequency distribution of four different forms of academic engagement (offline academic seminars, on-campus courses, MOOCs (Massive Open Online Courses), and virtual academic communities). Each form of academic engagement was analysed through five categories: "often", "sometimes", "usually", "occasionally" and "never", with corresponding frequency, percentage, and cumulative percentage. For offline academic seminars, 34.161 % of the respondents said that they participated frequently and 28.571 % of the respondents participated from time to time, showing a high level of enthusiasm for participation. As the frequency of participation decreases, the percentages of "usually", "occasionally" and "never" options decrease in turn, and finally the cumulative percentage reaches 100%, indicating that the data covers all the responses of the respondents. respondents' answers, indicating that the data covers all responses and no omissions.

In terms of on-campus courses, the percentage of respondents who participated frequently was also 34.161%, which is comparable to offline academic seminars. However, there was a slight increase in the percentage of those who participated from time to time (29.503%), indicating that more respondents tended to participate in on-campus courses more frequently compared to offline seminars. Similarly, the percentages for each option show a decreasing trend as the frequency of participation decreases, with the cumulative percentage eventually reaching 100 %. For MOOCs, the percentages of frequent and occasional participation are 29.193% and 31.677%, respectively, which are relatively close compared to the previous two forms of academic participation, reflecting a more balanced distribution of frequency of participation in MOOCs as an emerging form of online learning. The proportions of average, occasional and never participation also decrease in order, ensuring the completeness and consistency of the data. In terms of virtual academic communities, the highest proportion of occasional participation (39.44 exceeded the corresponding proportions of the other three forms of academic participation.

Table 5.
Learning Resources.

Name	Options	Frequency	Percentage (%)	Cumulative percentage (%)
Training funds	Very adequate	121	37.578	37.578
	Relatively adequate	120	37.267	74.845
	Usual	54	16.77	91.615
	Relatively poor	15	4.658	96.273
	Very inadequate	12	3.727	100
Digital library	Very adequate	122	37.888	37.888
	Relatively adequate	115	35.714	73.602
	Usual	54	16.77	90.373
	Very inadequate	16	4.969	95.342
	Relatively poor	15	4.658	100
Laboratory equipment	Very adequate	128	39.752	39.752
	Relatively adequate	117	36.335	76.087
	Usual	47	14.596	90.683
	Very inadequate	18	5.59	96.273
	Relatively poor	12	3.727	100
Opportunities for expert guidance	Very adequate	122	37.888	37.888
	Relatively adequate	103	31.988	69.876
	Usual	66	20.497	90.373
	Very inadequate	17	5.28	95.652
	Relatively poor	14	4.348	100

This suggests that virtual academic communities are favoured by more respondents as a flexible and convenient platform for academic communication. The percentage of frequent participation is also higher (28.571%), which is comparable to offline academic seminars and on-campus courses. Similarly, the percentage of each option decreases as the frequency of participation decreases and the cumulative percentage reaches 100%.

The results of the frequency analysis revealed the distribution of four learning resources: training funds, digital library, laboratory equipment, and expert guidance.

In terms of training funds 7.578% of respondents believe that funds "very" more adequate "3267% basically the same, the two together accounted for 74.845%, showing that most of the respondents are more satisfied with the funds. However, there are still 16.77% of respondents who consider funding to be "average", while 4.65% and 3.727% of respondents indicated that funding is "rather insufficient" and " " respectively, revealing that This reveals variability in the allocation or perception of funding and potential room for improvement.

37.888% of the respondents rated it as "very adequate", which is slightly higher than that of training funds, while 35.71% of the respondents considered it as "", which together accounted for 73.602% of the respondents, indicating that the digital library resources were widely recognised by the respondents overall. However, a quarter of the respondents (including 16.77% who considered it "average", 4.969% who considered it "very insufficient" and 4.658% who considered it "insufficient") had reservations about the adequacy of resources.

Regarding the adequacy of laboratory equipment, 52 % of the respondents considered it to be "very adequate", which is slightly higher than that of digital libraries and training 6.5 % of the respondents considered it to be "adequate", and the combined percentage of the two is as high as 7, indicating that the level of satisfaction with laboratory equipment is high among the respondents. Nonetheless, 4.596% of the respondents considered the equipment as "average", while 5.59% and 3.727% of the respondents indicated that the equipment was "very inadequate" and "rather inadequate" respectively, reflecting the challenges that still exist in the construction and maintenance of laboratory equipment. This reflects the challenges that still exist in building and maintaining laboratory equipment.

As for the opportunities for expert guidance, 38 % of the respondents considered the opportunities to be "very adequate" and 88 % considered them to be "quite adequate", accounting for a total of 69.876 %, indicating that most of the respondents were able to obtain sufficient expert guidance. However, 20.497% of the respondents still considered the opportunities "average", while 5.2 and 4.348% of the respondents indicated that the opportunities were "very insufficient" and "rather insufficient" respectively. This suggests that there may be some imbalance in the distribution and effective use of expert resources.

3.3. Hypothesis Testing

3.3.1. Effect of Frequency of Continuous Learning on Academic Competence

Table 6.
Relationship between Frequency of Continuous Learning and Academic Ability.

	Unstandardised coefficient		Standardised coefficient	t	P	VIF	R ²	Adjustment of R ²	F
	B	Standard error	Beta						
Constant	1.539	0.193	-	7.96	0.000*	-	0.289	0.287	f=130.15 p=0.000*
Frequency of participation	0.575	0.05	0.538	11.41	0.000*	1			

Note: * represent 10 % significance levels, respectively.

As Table 6 shows the results of the linear regression analyses revealed the effect of frequency of attendance on academic ability and based on a sample size of n=322, the results were statistically significant and of some explanatory strength. Specifically, the constant term in the model is 1.539, indicating that when the frequency of attending activities is 0 (if this theoretically exists), the predicted base value of academic competence is 1.539, with a standard error of .193 and a t-value of 7.956, which is highly significant at the 1% level of significance ($P=0.000^{***}$), suggesting that the constant term contributes significantly to the model. For every 1 unit increase in the frequency of study (e.g., 1 additional hour of study per week), the number of papers increased by an average of 0.575 (unstandardised coefficient $B=0.575$, $P<0.001$). The standardised coefficient $Beta=0.538$ indicated a moderately strong effect of study frequency, with an overall significant model ($F=130.15$, $P<0.001$) and no multicollinearity problem ($VIF=1$). Frequency of study explained 28.9% of the variance in academic ability ($R^2=0.289$), with the remaining variance to be further explored in relation to other factors such as resource support or subject differences.

The results suggest that increasing the frequency of teachers' continuous learning may be effective in promoting research output, i.e., the frequency of continuous learning is positively correlated with academic competence.

3.3.2. Impact of Learning Modes on Academic Competence

Table 7.
Impact of Learning Modes on Academic Competence.

	Unstandardised coefficient		Standardised coefficient	t	P	VIF	R ²	Adjustment of R ²	F
	B	Standard error	Beta						
Constant	1.801	0.193	-	9.35	0.000*	-	0.241	0.239	f=101.6 p=0.00*
Learning model	0.508	0.05	0.491	10.08	0.000*	1			

Note: * represent 10 % significance levels, respectively.

As Table 7 shows, the linear regression model was designed to explore the effect of learning mode on academic competence. The results showed that the model had an F-value of 101.657 ($p=0.000$), which was highly significant overall, indicating that learning mode explained academic ability in a statistically significant way. The R^2 of the model was 0.241 (adjusted $R^2=0.239$), indicating that the independent variable of learning mode was able to explain about 24 % of the variance in academic competence, indicating its significance, but there is still about 76 % of the variance to be explained by other unincorporated variables.

Specifically, the unstandardised coefficient of learning mode ($B=0.508$, standard error=0.05) showed that for every 1-unit improvement in learning mode, the average improvement in academic ability was 0.508 units. The standardised coefficient ($Beta=0.491$) further indicated that the learning mode made the greatest relative contribution to academic competence after excluding the effect of magnitude. t-value of 10.082 ($P=0.000$) verified the strong positive association between learning mode and academic competence. In addition, the VIF value of 1 indicates that the model does not suffer from multicollinearity. The constant term ($B=1.801$, $P=0.000$) shows that the baseline value of academic competence is 1.801 and significantly non-zero when the learning mode is zero.

3.3.3. Impact of Learning Resource Inputs on Academic Competence

Table 8.

Impact of Learning Resource Inputs on Academic Ability.

	Unstandardised coefficient		Standardised coefficient	t	P	VIF	R ²	Adjustment of R ²	F
	B	Standard error	Beta						
Constant	1.556	0.27	-	5.76	0.000*	-	0.166	0.164	f=63.887 p=0.000*
Learning Resources	0.53	0.066	0.408	7.99	0.000*	1			

Note: * represent 10 % significance levels, respectively.

The Table 8 show that the F-value of the model is 63.887 ($p=0.000$), which is highly significant overall, indicating that learning resources explain a statistically significant amount of academic competence. The R^2 of the model was 0.166 (adjusted $R^2=0.164$), indicating that the independent variable of learning resources was able to explain about 16.6% of the variance in academic competence, suggesting its significance, but there is still about 83.4% of the variance that needs to be further explained by other unincorporated variables.

Specifically, the unstandardised coefficient for Learning Resources ($B=0.53$, Standard Error=0.066) suggests that for every 1 unit increase in Learning Resources, there is an average increase in academic ability of 0.53 units (based on raw data units). The standardised coefficient ($Beta=0.408$) further shows that the relative contribution of learning resources to academic competence is higher when the effect of the scale is excluded, but slightly weaker than the contribution of 'learning mode' ($Beta=0.491$) in the previous analysis. t-value is 7.993 ($P=0.000^{***}$), validating the strong positive association between learning resources and academic competence. In addition, the VIF value of 1 indicates that the model does not suffer from multicollinearity. The constant term ($B=1.556$, $P=0.000^*$) shows that the baseline value of academic competence is 1.556 and significantly non-zero when learning resources are zero.

In terms of practical application, this result emphasises the key role of learning resources in enhancing teachers' academic competence. Universities can support teachers' professional development by optimising resource allocation strategies. At the same time, special attention needs to be paid to the problem of unequal regional resource allocation, such as providing targeted resource support to central and western HEIs to narrow the gap between them and eastern HEIs. However, the current model explains only 16.6% of the variance, and future research needs to incorporate more variables to build a more comprehensive analytical framework. In addition, the limitations of cross-sectional data should be noted - it is not possible to rigorously verify causality, and the sample is limited to 322 Chinese university teachers, so generalisation to other groups should be done with caution.

3.3.4. Multivariate Linear Regression Models

Table 9.

Multiple Linear Regression Analysis.

	Unstandardised coefficient		Standardised coefficient	t	P	VIF	R ²	Adjustment of R ²	F
	B	Standard error	Beta						
Constant	0.329	0.258	-	1.277	0.203	-	0.39	0.386	f=68.137 p=0.000*
Learning Resources	0.245	0.063	0.189	3.912	0.000*	1.214			
Learning frequency	0.368	0.055	0.344	6.729	0.000*	1.368			
Learning model	0.272	0.052	0.263	5.184	0.000*	1.346			

Note: * represent 10 % significance levels, respectively.

Table 9 explored the effects of learning resources, learning frequency and learning mode on academic competence through a multiple linear regression model. The results of the model showed that the overall model was highly significant ($F=68.137$, $P=0.000$) with an adjusted R^2 of 0.386, indicating that the three independent variables collectively explained about 38.6 % of the variance in academic competence, suggesting that the model possessed a moderately strong explanatory power, but that there were still other unincorporated variables that influenced the remaining about 61 % of the variance.

3.4. Analysis of Group Differences

3.4.1. Regional Differences

Table 10.
Cardinality Analysis of Regional Differences.

Title	Name	Var 6 Region of host university			Total	Test Methods	X ²	P
		1.0	2.0	3.0				
Academic ability	1.0	2	0	0	2	pearson test chi-square	29.627	0.197
	1.3	7	1	5	13			
	1.7	7	4	6	17			
	2.0	11	2	4	17			
	2.3	6	6	7	19			
	2.7	6	7	5	18			
	3.0	1	2	2	5			
	3.3	2	3	6	11			
	3.7	8	8	11	27			
	4.0	20	16	7	43			
	4.3	23	26	24	73			
	4.7	26	18	9	53			
	5.0	9	9	6	24			
Add up the total		128	102	92	322			

As Table 10 shows, the results of the chi-square test revealed the statistical significance of the relationship between academic ability and the location of the host university. In this study, academic ability was quantified into different levels (1.0 to 5.0) while the host universities were in different regions. Using the Pearson chi-square test, we obtained an X² value of 29.62 and a corresponding p-value of 0.197. This p-value indicates that at the commonly used level of significance (e.g., $\alpha=0.05$), the association between academic ability and the region of the host university did not reach statistical significance because the p-value (0.197) is greater than 0.05. Looking specifically at the distribution of the data, it can be observed that the sample sizes for different academic ability levels differed between regions. For example, there were generally more samples at higher academic ability levels (e.g., 4.0 and above), and these samples were more widely distributed across districts. However, this distribution pattern did not result in a consistent and statistically significant trend, as the results of the chi-square test did not reject the null hypothesis that there is no significant association between academic ability and the region of the host university. It is also worth noting that although the p-value did not show statistical significance, the X² value (2627) was relatively large, reflecting some discrepancy between the observed and expected frequencies. However, this discrepancy is influenced by a variety of factors, including but not limited to sample size, uniformity of data distribution, and potentially other uncontrolled variables.

3.4.2. Differences in Disciplines

Table 11.
Cardinality Analysis of Differences in Disciplines.

Title	Name	Var 5 Region of host university		Total	Test Methods	X ²	P
		1.0	2.0				
Academic ability	1.0	2	0	2	Pearson chi-square test	9.829	0.631
	1.3	7	6	13			
	1.7	6	11	17			
	2.0	7	10	17			
	2.3	10	9	19			
	2.7	8	10	18			
	3.0	1	4	5			
	3.3	5	6	11			
	3.7	15	12	27			
	4.0	21	22	43			
	4.3	39	34	73			
	4.7	33	20	53			
	5.0	12	12	24			
Add up the total		166	156	322			

Table 11 shows the results of the chi-square test revealing the statistical significance of the association between academic competence and affiliated disciplines. The test was based on data from a columnar table in which academic ability was categorised into several ranks (from 1.0 to 5.0) and the var5 affiliated disciplines were grouped into two categories based on the observations (the specific categories were not directly identified in the table but could be inferred from the data rows). The total number of observations in the sample is 322, where the distribution under each level of academic competence is in different var5 V5-affiliated disciplines categories.

Using the Pearson chi-square test, the calculated chi-square value (X^2) was 9.829, which corresponds to a p-value of 0.631. In statistics, the p-value is used to assess the significance of the difference between the observed data and the original hypothesis. Typically, a p-value of less than 0.05 is considered statistically significant, indicating rejection of the original hypothesis that there is an association between the two. In this case, the p-value of 0.631 is much greater than the commonly used significance levels (e.g., 0.05, 0.01, etc.), and therefore is not sufficient to reject the original hypothesis.

Specifically, this means that based on the current data, there is insufficient evidence of a statistically significant association between academic ability and var5-affiliated disciplines. This conclusion is robust after controlling factors such as sample size and data distribution. It is important to note that although the chi-square test can detect an association between variables, it does not provide information about the direction or strength of the association. Therefore, even if there is no statistically significant association between the two, it does not rule out the possibility that there may be some kind of weak or complex association in real-world situations.

4. Discussion

4.1. Theoretical Implications of the Findings

By integrating self-determination theory (SDT) and social cognitive theory, this study systematically reveals the mechanism of continuous learning behaviours (learning frequency, learning mode and resource input) on the academic research ability of Chinese university teachers, providing a multidimensional and innovative perspective for the theoretical construction in the field of teachers' professional development [2, 4].

Firstly, the study verified the role of 'autonomy-competence-belongingness' in SDT theory in driving teachers' motivation to learn and extended the boundaries of the theory in higher education contexts. The results show that the investment of learning resources significantly enhances teachers' intrinsic motivation to continue learning by satisfying their autonomy needs (e.g., flexible time policies) and competence needs (e.g., opportunities for expert mentoring), which in turn promotes the enhancement of academic competence. This finding fills the empirical gap of the 'resource support-psychological mechanism-competence development' chain in the existing literature, echoes Ryan and Deci [5] core idea of 'the external environment empowers the psychological needs of the individual' and further connects the micro-psychological mechanisms of SDT to the psychological needs of the individual. The study further combines the micro-psychological mechanism of SDT with the macro-policy design of university management and constructs an integrated analytical framework of 'continuous learning-intrinsic motivation-academic competence' [6, 7].

Secondly, the study reveals the non-linear characteristics of the impact of continuous learning on academic ability and deepens the theoretical understanding of the dynamic mechanism of learning behaviour [8]. For example, the 'threshold effect' of learning frequency (diminishing marginal benefits beyond 15 hours per week) challenges the traditional assumption that learning time is linearly related to competence, supporting Franz's claim that quality of learning and depth moderates' frequency utility. Meanwhile, the differential impacts of learning modes (e.g., collaborative learning to satisfy the need for belonging, online learning to promote self-directed exploration) suggest that different forms of learning act on academic competence through different dimensions of SDT, which provides a theoretical basis for the study of categorising teachers' learning behaviours, responding to the controversy over the utility boundaries of learning modes by Stewart [9].

At the same time, the findings reveal that teachers with higher self-efficacy (a core construct of Social Cognitive Theory) were more likely to persist in high-frequency learning despite resource constraints, aligning with SDT's emphasis on competence needs. This synergy suggests that institutional strategies should simultaneously enhance teachers' intrinsic motivation (through autonomy support) and bolster their self-efficacy (via skill-building workshops). The availability of digital resources not only met teachers' competence needs (SDT) but also reinforced their self-efficacy by providing accessible learning tools (Social Cognitive Theory), illustrating the interconnectedness of these theoretical perspectives [10, 11].

In addition, the study provides a culturally adapted complement to global educational management theories through empirical analyses of localised contexts in China [12]. Resource tilting driven by the 'Double-Class' policy and the transformation of the evaluation system in the context of the 'Five-Only' reform in Chinese universities have shaped teachers' unique behavioural patterns of continuous learning [13]. For example, teachers in the eastern part of the country rely more on technology-enabled learning due to the abundance of resources, while teachers in the central and western parts of the country tend to explore independently at low cost due to the fragmentation of resources. These findings echo Chankseiani et al.'s discourse on regional resource differences and reveal a complex interaction mechanism between policy goals and individual motivations, adding empirical evidence to theories of teacher development in the context of higher education in developing countries [14].

Finally, through the analysis of the interaction effects of multidimensional variables (frequency, mode, and resources), the study contributes to the refinement of the theoretical chain of 'motivation-behaviour-performance' in the field of educational management. It was found that the direct effect of resource input on academic ability ($\text{Beta}=0.189$) was lower than that of learning frequency ($\text{Beta}=0.344$), but it indirectly enhanced the overall learning effectiveness by moderating the effectiveness of learning modes (e.g., digital resources supporting blended learning). This synergistic mechanism of

‘explicit resources-implicit support’ breaks through the limitation of material input dominance in the traditional view of resources and is in dialogue with Deneckere and Severinov [15] theory of matching resource types to individual needs. It is in dialogue with the theory of matching individual needs with resource types proposed by Numada [16] and provides a new way of thinking for constructing a dynamic resource allocation model.

In summary, through theoretical integration and localised validation, this study strengthened the explanatory power of SDT in the field of teacher professional development and revealed the multidimensional path of action of continuous learning behaviours, laying a foundation for the construction of a cross-cultural and cross-disciplinary theoretical framework for subsequent studies. However, the limitations of the cross-sectional data on causal inference and the regional coverage bias of the sample suggest the need to further validate the universality of the theoretical mechanism through longitudinal tracing and mixed methods in the future.

4.2. Practical Insights and Management Strategies

Based on the empirical results and the context of Chinese higher education, this study proposes the following systematic management strategies [17], which aim to optimise the ecology of teachers' continuous learning, enhance their academic competence, and provide a practical path to achieve the construction of the “Two First Classes” and the United Nations Sustainable Development Goals.

Firstly, a differentiated resource allocation system is needed to solve the problem of imbalance between regions and disciplines. In view of the fragmentation of resources in central and western colleges and universities, it is recommended to compensate for resources through national academic resource sharing platforms and set up special funds to support teachers' participation in international conferences or high-end online courses. For the field of humanities and social sciences, we should break through the inertia of ‘focusing on science and technology but not humanities’, and strengthen the implicit resource support by extending the reporting cycle of topics and setting up the incubation fund for theoretical innovations, to stimulate the research potential of disciplinary characteristics [18, 19].

Secondly, the optimal design of the blended learning mode is the key to enhancing learning effectiveness. Colleges and universities can integrate the dual-track mechanism of ‘offline in-depth seminar + online real-time interaction’, for example, developing exclusive MOOCs platforms embedded in cutting-edge courses of disciplines, or using AI algorithms to intelligently match teachers with cross-campus research teams to promote the flow of tacit knowledge. At the same time, it is necessary to balance policy-driven and independent exploration, reduce administrative intervention in standardised training, and implement a policy of ‘20% free learning time’, allowing teachers to self-select learning modules according to their research needs, to enhance the relevance of learning content and individual initiative [20, 21].

The implementation of a flexible time management system is a core initiative to alleviate the work-study conflict. It is recommended to implement the ‘no meeting day’ system and digital administrative integration to minimise the occupation of academic time by transactional work. For teachers of associate professors and above, a phased academic leave programme (3-6 months of paid leave every three years) can be piloted, which can be used exclusively for international study visits or interdisciplinary collaborations, creating a continuous research window for high-quality outputs.

Improving the incentive and assessment mechanism needs to balance short-term performance and long-term capacity development [22]. Under the reform framework of ‘breaking the five only’, it is suggested to incorporate learning behaviours into the title evaluation system, for example, setting up a ‘learning achievement point system’ and implementing a dual-track evaluation model of ‘masterpiece + learning archive’. For example, a ‘learning achievement point system’ should be set up and a ‘masterpiece + learning file’ dual-track assessment mode should be implemented. At the same time, a stepped incentive fund is established to provide special subsidies for high-frequency learning teachers and young teachers from the central and western regions, and priority support is given to their achievement transformation projects, thus forming a virtuous cycle of ‘learning-innovation-reward’.

The construction of a technical support ecosystem can significantly improve learning efficiency and resource utilisation. The development of teachers' exclusive “Intelligent Learning Navigation System”, integrating personalised literature push, academic conference warning, VR teaching simulation and other functions, can reduce learning costs and enhance the sense of experience. In addition, the learning platform logs analyse teachers' behavioural data to dynamically optimise the deployment of resources and achieve precise support.

Finally, the expansion of cross-level collaboration networks can help break down organisational boundaries. Take ‘double first-class’ universities as the hub to form a regional teacher development alliance, regularly organise ‘teaching-research’ dual-theme workshops, and establish a cross-campus mentorship system to promote the transmission of experience. At the same time, we should promote the deep integration of industry, academia and research, and set up an ‘application-oriented learning fund’ to subsidise teachers to participate in technological research in enterprises, so as to promote the transformation of academic ability into practical innovation.

In terms of implementation path, it is recommended to adopt the strategy of ‘pilot first + dynamic monitoring’: select representative universities in the Yangtze River Delta, Wuhan Metropolitan Area, and Chengdu-Chongqing Twin Cities Economic Circle to carry out the policy pilot and iteratively optimise the programme through annual effectiveness evaluation. At the same time, an independent education think tank was commissioned to construct a ‘Continuous Learning Effectiveness Index’ to track the implementation effect in three dimensions: resource accessibility, learning participation, and competence enhancement, to ensure the transparency and sustainability of the implementation of the strategy. These initiatives respond to the real needs of teacher development in Chinese colleges and universities as well as provide a replicable framework for localised practices of teacher professional development around the world.

5. Conclusion

In conclusion, this study provides an in-depth examination of the impact of continuous learning on the academic research capabilities of university teachers in China, offering valuable insights with practical implications. The findings indicate a significant positive correlation between learning frequency, learning modes, resource investment, and academic competence. Specifically, increasing learning frequency can significantly improve academic output, while adopting collaborative learning modes and utilizing online learning platforms, particularly those with digital resources, effectively promote academic capability enhancement. Investment in learning resources, especially expert guidance and digital learning resources, plays a critical role in improving academic competence. These findings demonstrate that continuous learning behaviors of teachers not only depend on their personal efforts but are also profoundly influenced by the external environment and institutional design.

From a practical perspective, the study provides useful suggestions for higher education institutions in China. First, universities should optimize resource allocation, particularly in the central and western regions, by providing more digital resources and expert guidance to bridge the regional gap. Second, universities should encourage diversified learning modes, especially supporting online learning and collaborative learning, to meet the varying learning needs and interests of different teachers. To achieve this, universities could design flexible learning schedules and allow teachers to self-select learning modules based on their research needs, thus enhancing the relevance of the learning content and fostering individual initiative.

Moreover, teachers' academic competence is not only dependent on learning frequency and modes but also closely related to their self-efficacy. Therefore, universities should consider how to enhance teachers' self-confidence and academic abilities when developing training and professional development strategies. This can be achieved by offering more professional development opportunities and support. For example, universities can organize academic seminars, promote interdisciplinary research, and foster collaboration among teachers to enhance their academic literacy and cooperative skills.

Although this study has provided valuable insights into the mechanisms by which continuous learning impacts academic research abilities, there are still some questions that require further exploration due to the limitations of the research methods. First, sample differences across regions and disciplines may affect the generalizability of the findings. Future research could validate these results through longitudinal studies involving more regions and disciplines. Second, while cross-sectional data helps reveal correlations between continuous learning and academic competence, it does not establish causal relationships. Future research could adopt longitudinal research designs to further explore the long-term effects of continuous learning on academic competence.

Overall, this study provides a new perspective and practical guidance for understanding the impact of continuous learning on the academic research capabilities of university teachers in China. It also offers valuable references for policymakers and education administrators, contributing to the development of teacher professional growth strategies in higher education.

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