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PAPER

Evaluation of Information Skills and Innovative Literacy Cultivation of Digital Talent in Universities

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ABSTRACT

In the context of globalization and informatization, cultivating the information ability and innovative literacy of university digital talents is of great significance for cultivating talents in supply chain majors. However, some shortcomings remain in the information ability evaluation and innovative literacy cultivation of university talents in the current education system. In this context, this study conducted in-depth research on the information ability evaluation of digital talents in universities and its impact on the cultivation of innovative literacy. The fuzzy comprehensive evaluation method was first adopted to make a quantitative evaluation of the information ability of university digital talents, which aimed to compensate for the shortcomings of existing qualitative evaluation methods. Then, regression models, as well as mediating and moderating effect models, were constructed to deeply analyze the impact of information ability on innovative literacy cultivation, aiming to reveal the complexity of the impact mechanism. This study aimed to provide new perspectives and methods for theory and practice, thereby improving the information ability evaluation system and the innovative literacy cultivation mechanism of digital talents in universities. This study is not only theoretically significant, but it also provides a practical reference for universities in cultivating talents in supply chain major.

KEYWORDS

digital talents, information ability evaluation, innovative literacy, fuzzy comprehensive evaluation method, regression models, mediating effect models, moderating effect models, supply chain major

1 INTRODUCTION

With the rapid development of digitization and informatization, higher requirements have been put forward for the information ability and innovative literacy of university talents, especially supply chain professionals [1–4], mainly because the practical operation of supply chain management involves many complex technical problems, such as big data processing, artificial intelligence technology application,

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process optimization, etc., the solution of which is inseparable from the precise control of information technology and the application of innovative thinking. Therefore, the cultivation of information ability and innovative literacy among university digital talents has become an important topic that must be urgently addressed in the current educational field [5–8].

However, there are still some unsatisfactory aspects of information ability evaluation and innovative literacy cultivation among university talents in the current education system [9] [10]. Current information ability evaluation methods, for example, often remain at the theoretical level, which not only lacks an assessment of practical operation ability but also cannot accurately evaluate students' information processing and analysis abilities and other practical skills. At the same time, although there is some theoretical teaching for innovative literacy cultivation, there is no effective practical link that can truly cultivate the innovative thinking and problem-solving abilities of students [11–13].

Existing research methods have certain limitations for solving the above-mentioned problems. In terms of information ability evaluation, existing research methods mostly adopt qualitative analysis, and few of them use quantitative analysis methods, such as fuzzy comprehensive evaluation (FCE) method [14–17]. For the analysis of factors influencing innovative literacy cultivation, most existing research methods focus on a single influencing factor only, with little research on the interaction effect of multiple factors and moderating factors, making it difficult to comprehensively and accurately reveal the true mechanism that affects innovative literacy cultivation [18–21].

This study executed research in two aspects to improve the situation. First, the FCE method was used to evaluate the information ability of digital talents in universities, which accurately evaluated the practical skills of students, such as information processing and analysis abilities, thus improving the pertinence and effectiveness of the evaluation system. Second, this study constructed regression models as well as mediating and moderating effect models to deeply analyze the impact of the information ability of digital talents in universities on their innovative literacy cultivation, with the aim of better understanding the various factors that affect innovative literacy cultivation and their interaction effect.

The value of this study is mainly reflected in two aspects. First, it provides new perspectives and methods for theoretical research, which helps to improve the information ability evaluation system and innovative literacy cultivation mechanisms for digital talents in universities. Second, it has guiding significance for practice by providing targeted education and training suggestions for university digital talents and practical reference for talent cultivation in supply chain majors.

2 INFORMATION ABILITY EVALUATION OF DIGITAL TALENTS IN UNIVERSITIES

Information ability evaluation index systems for university digital talents can be constructed from multiple perspectives. This study's index system includes four first-level indexes and sixteen second-level indexes. When establishing the system, the index selection principle should focus on comprehensiveness, objectivity, scientificity, and operability. First, indexes should comprehensively cover all aspects of information ability. Second, they should objectively reflect the true level of informational ability. Third, their selection should be based on scientific theory and practical experience. Finally, the selected indexes should have a certain degree of operability and be obtained through actual observation and measurement. Based on the characteristics of each index, appropriate quantitative methods were selected, such as scoring and percentage methods, etc.

At the first level, the overall goal factor set $S = (S1, S2, S3, S4)$ = {information acquisition, processing, application, and innovation abilities}.

At the second level, the subgoal factor sets were as follows:

$N = (N1, N2, N3, N4)$ = {Search strategies (effectively formulating and executing information search strategies), retrieval skills (mastering various information retrieval tools and skills), data recognition (distinguishing valid and invalid information sources), and data collection (efficiently collecting various types of information data)};

$V = (V1, V2, V3, V4)$ = {Data analysis (effectively understanding and analyzing the collected information), information organization (organizing and classifying information reasonably), information extraction (extracting core content from a large amount of information), and information transformation (transforming information into knowledge for individual knowledge accumulation)};

$F = (F1, F2, F3, F4)$ = {problem solving (solving practical problems using information processing results), decision support (using information results to assist decision-making), practical operation (applying information technology to practical work), communication and exchange (effectively using information for communication and exchange)};

$R = (R1, R2, R3, R4)$ = {innovative thinking (generating new ideas and viewpoints by combining information results), technological innovation (using new information technology to improve workflow), product innovation (using information for product or service innovation), and business innovation (using information for business model innovation)}.

The evaluation set was then developed, which usually contained a group of words or phrases describing information ability level, such as "very satisfied," "relatively satisfied," "moderately satisfied," "not very satisfied," and "very dissatisfied." A fuzzy number was assigned to each evaluation word to quantify its meaning. For the models in this study, a five-level evaluation set was developed namely $C = (C1, C2, C3, C4, C5)$ = {very satisfied, relatively satisfied, moderately satisfied, not very satisfied, very dissatisfied}.

Then the analytic hierarchy process (AHP) was used to rank the importance of each evaluation index, and the weight of each index was determined based on this. The specific process included constructing a judgment matrix, calculating eigenvalues and eigenvectors, and normalizing them to obtain the weight of each index.

Each index was evaluated, and the results were converted into fuzzy numbers to form a fuzzy judgment matrix. Two-layer elements of indexes were evaluated separately by distributing expert questionnaires. After sorting through the questionnaire results, conclusions were drawn.

$$E_u = \begin{pmatrix} e_{u11} & e_{u12} & \cdots & e_{u1b} \\ e_{u21} & e_{u22} & \cdots & e_{u2b} \\ e_{u31} & e_{u22} & \cdots & e_{u3b} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ e_{ub1} & e_{ub2} & \cdots & e_{ubb} \end{pmatrix}, (u = 1,2,3,4) \tag{1}$$

Fuzzy comprehensive operation of the fuzzy judgment matrix and the weight vector was performed, which obtained a fuzzy comprehensive evaluation vector. The fuzzy transformation rule in fuzzy mathematics was usually adopted as the specific operation method:

$$N_u = S_u \times E_u = (b_{u1}, b_{u2}, b_{u3}, b_{u4}, b_{u5}), (u = 1,2,3,4)$$

$$E = \begin{pmatrix} N_1 \\ N_2 \\ N_3 \\ N_4 \end{pmatrix}, b = (1,2,3,4) \tag{2}$$

The fuzzy comprehensive evaluation vector was transformed into specific evaluation result. The maximum membership principle was adopted, i.e. selecting the evaluation word with the highest membership as the final evaluation result. After finding the maximum component $MAX\ \{n_u\}$ and the second largest component $SE\ \{n_u\}$ in $N = (n_1, n_2, n_3, n_4, n_5)$, the vector sum $\sum_{u=1}^{b} n_u$ of the evaluation set was calculated. Finally, the maximum membership degree β was calculated, i.e. $\beta = b\alpha - 1/2\varepsilon(b-1)$, with $\alpha = MAn_u / \sum_{u=1}^{b} n_u$ and $\varepsilon = SEn_u / \sum_{u=1}^{b} n_u$.

3 ANALYZING THE IMPACT OF INFORMATION ABILITY ON INNOVATIVE LITERACY CULTIVATION

In today's information society, information ability and the innovative literacy of digital talents in universities are key factors in promoting economic development and social progress. For digital talents in universities, good information ability helps them better access, process, and apply information, further promoting innovation activities. However, there is relatively little research on how information ability affects innovative literacy cultivation, and some gaps exist in specific quantitative models.

In this context, this study chose to construct regression models as well as mediating and moderating effect models. The regression models revealed a direct relationship between information ability and innovative literacy, helping us to understand to what extent information ability improvement enhanced innovative literacy. The mediating effect models helped further understand the mediating mechanism in this relationship, i.e., the paths through which information ability affected innovative literacy. The moderating effect models revealed how information ability affected innovative literacy differently under different conditions, allowing for better strategy adaptation in practical operations.

3.1 Selection of main variables

To analyze the impact of the information ability of university digital talents on their innovative literacy cultivation, this study set the following variables:

- Explanatory variables (independent variables), including information acquisition and application abilities, were quantified through the evaluation index system and represented by scores ranging from 1 to 5.

- Explained variable (dependent variable), i.e., innovative literacy, which was quantified through the innovative literacy evaluation system and was represented by scores ranging from 1 to 5. For example, it was evaluated by the number of innovative projects, products, and schemes.
- The mediating variable, i.e., information processing ability, was quantified through the evaluation index system and was represented by scores ranging from 1 to 5.
- Moderating variables included learning environment and motivation, which were quantified through the learning environment satisfaction and learning motivation questionnaire scores of students and represented by scores ranging from 1 to 5.
- Control variable, which includes the following aspects: First, gender, which was represented in binary, with 1 representing male and 0 representing female. Second, grade was represented by numbers ranging from 1 to 4, with 1 representing a freshman, 2 representing a sophomore, and so on. Third, major was represented by the dummy variable. Each major was a variable, with 1 representing the major's corresponding variable and 0 representing other variables. Fourth, teaching quality was quantified by students' satisfaction with teaching quality and was represented by scores ranging from 1 to 5. Fifth, learning time was represented in learning time (hours) per week. Sixth, practical experience was quantified by the number of practical projects and represented in quantity. Seventh, extracurricular activities were quantified by the number of extracurricular activities that participated and were represented in quantity.

3.2 Regression models

Based on the above variable settings, the following two hypotheses to be verified were proposed:

Hypothesis 1: There is a positive relationship between information acquisition ability and innovative literacy.

This hypothesis is based on theoretical and practical observations; that is, stronger information acquisition ability often means a stronger ability to discover new knowledge and information, which is crucial for innovation activities. Therefore, it is expected that the stronger the ability to obtain information, the higher the innovative literacy.

Hypothesis 2: There is a positive relationship between information application ability and innovative literacy.

This hypothesis is based on theoretical and practical observations; that is, stronger information application ability often means a stronger ability to use new knowledge and information, which is also crucial for innovation activities. Therefore, it is expected that the stronger the information application ability, the stronger the innovative literacy.

These two hypotheses were verified through the regression models given below, which helped in understanding how various dimensions of information ability affected innovative literacy, thereby providing a basis for further improving information ability and innovative literacy among university digital talents.

Let CX_{uy} be the innovative literacy level of university digital talent u in year y; AV_{uy} be the information acquisition ability of u in year y; $\alpha_1 > 0$ be the information acquisition ability promoting innovative literacy of university digital talents; $\alpha_1 < 0$ be the information acquisition ability inhibiting innovative literacy; BL_{uy} be the control variables of university digital talents, such as gender, grade, and major; $\sum IN$ and $\sum YE$ be the controlled information technology and annual effect, respectively; γ_{uy} be the random perturbation term. To test hypothesis 1, the following model was constructed to explore the impact of information acquisition ability on the innovative literacy of digital talents in universities:

$$CX_{uy} = \alpha_0 + \alpha_1 AV_{uy} + \alpha_2 BL_{uy} + \sum IN + \sum YE + \gamma_{uy} \tag{3}$$

Let KH_{uy} be the information application ability of university digital talent u in year y, $\alpha_1 > 0$ be the information application ability promoting innovative literacy of university digital talents, and $\alpha_1 < 0$ be the information application ability hindering innovative literacy. To test hypothesis 2, the following model was constructed to explore the impact of information application ability on the innovative literacy of digital talents in universities:

$$CX_{uy} = \alpha_0 + \alpha_1 KH_{uy} + \alpha_2 BL_{uy} + \sum IN + \sum YE + \gamma_{uy} \tag{4}$$

Information acquisition and application abilities were integrated into a model to verify the impact of information ability of university digital talents on innovative literacy, which also preliminarily confirmed the robustness of Hypotheses 1 and 2:

$$CX_{uy} = \alpha_0 + \alpha_1 GYS_{uy} + \alpha_2 KH_{uy} + \alpha_3 BL_{uy} + \sum IN + \sum YE + \gamma_{uy} \tag{5}$$

3.3 Mediating effect models

Based on the above variable settings, the following two hypotheses to be verified were set:

Hypothesis 3a: Information processing ability serves as a bridge between information acquisition ability and innovative literacy.

This hypothesis is based on the theory that information processing ability may serve as a bridge connecting information acquisition ability and innovative literacy; that is, individuals with high information processing ability may better utilize the obtained information to improve their innovative literacy. Thus, it is expected that the mediating effect of information processing ability on the relationship between information acquisition ability and innovation competence can be demonstrated by a mediating effect model.

Hypothesis 3b: Information processing ability serves as a bridge between information application ability and innovative literacy.

This hypothesis is based on the theory that information processing ability may play a crucial role between information application ability and innovative literacy; that is, individuals with strong information processing ability may more effectively transform applied information into innovative literacy. Therefore, it is expected that the mediating effect of information processing ability on the relationship between information application ability and innovative literacy can be demonstrated through a mediating effect model.

To test hypotheses 3a and 3b and explore the mediating effect of information processing ability, the following three models were constructed to confirm this path. Equation 6 was used to test the impact of information acquisition and application abilities on the innovative literacy of digital talents in universities. If coefficient β_1 was significant, Equation 7 was used to test the impact of the explanatory variable (information acquisition and application abilities) on the mediating variable (information processing ability), and all explanatory and mediating variables were included in Equation 8. If coefficients T_1 and T_2 were both significant, the mediating effect was partial; if coefficient T_2 was significant but T_1 was insignificant, the mediating effect was complete; and if coefficient T_2 was not significant, the mediating effect was impossible. Let Z_{uy} be the explanatory variable, GYS_{uy} be the information acquisition ability, and KH_{uy} be the information application ability, then there were:

$$EF_{uy} = \beta_0 + \beta_1 Z_{uy} + \beta_2 BL_{uy} + \sum IN + \sum YE + \gamma_{uy} \tag{6}$$

$$JX_{uy} = \alpha_0 + \alpha_1 Z_{uy} + \alpha_2 BL_{uy} + \sum IN + \sum YE + \gamma_{uy} \tag{7}$$

$$EF_{uy} = T_0 + T_1 Z_{uy} + T_2 JX_{uy} + T_3 BL_{uy} \sum IN + \sum YE + \gamma_{uy} \tag{8}$$

3.4 Moderating effect models

Based on the above variable settings, the following four hypotheses were set in this study:

Hypothesis 4a: The learning environment regulates the relationship between information acquisition ability and innovative literacy.

The premise of this hypothesis is that the learning environment may influence the degree to which information acquisition ability affects innovative literacy. In an excellent learning environment, information acquisition ability may more easily transform into innovative literacy. By testing this hypothesis, it is expected that the moderating effect of the learning environment can be discovered.

Hypothesis 4b: Learning motivation regulates the relationship between information acquisition ability and innovative literacy.

This hypothesis is based on the idea that learning motivation may influence the impact of information acquisition ability on innovative literacy. Individuals with high learning motivation may be better able to transform their information acquisition ability into innovative literacy. By testing this hypothesis, it is expected that the moderating effect of learning motivation can be discovered.

Hypothesis 5a: The learning environment regulates the relationship between information application ability and innovative literacy.

This hypothesis is based on the extent to which the learning environment influences the impact of information application ability on innovative literacy. In a high-quality learning environment, information application ability may more easily transform into innovative literacy. By testing this hypothesis, it is expected that the moderating effect of the learning environment on the relationship between information application ability and innovative literacy can be discovered.

Hypothesis 5b: Learning motivation regulates the relationship between information application ability and innovative literacy.

This hypothesis is based on the idea that learning motivation may affect the impact of information application ability on innovative literacy. Individuals with high learning motivation may be more able to transform their information application ability into innovative literacy. By testing this hypothesis, it is expected that the moderating effect of learning motivation on the relationship between information application ability and innovative literacy can be discovered.

Equation 9 was constructed to test whether the learning environment played a moderating role in the relationship between information ability and the innovative literacy of university digital talents, i.e., hypotheses 4a and 4b. Let β_2 be the intersection term coefficient in the equation, i.e., the moderating effect of the learning environment. If coefficient β_2 was significantly positive, it indicated that learning environment played a positive moderating role in the relationship between information ability and innovative literacy of university digital talents; if the coefficient was significantly negative, it indicated the negative moderating effect of learning environment; and if the coefficient was not significant, it indicated that the moderating effect of learning environment was not possible.

$$\begin{aligned} EF_{uy} = {} & \beta_0 + \beta_1 Z_{uy} + \beta_2 Z_{uy} * VDP_{uy} + \beta_3 VDP_{uy} + \beta_4 BL_{uy} \\ & + \sum IN + \sum YE + \gamma_{uy} \end{aligned} \tag{9}$$

Equation 10 was constructed to test the moderating effect of learning motivation on the relationship between information ability and innovative literacy of digital talents in universities, i.e., hypotheses 5a and 5b. Let β_2 be the interaction term coefficient in the equation, i.e., the moderating effect of learning motivation. If coefficient β_2 was significantly positive, it indicated that learning motivation played a positive moderating role in the relationship between information ability and innovative literacy of digital talents in universities; if the coefficient was significantly negative, it indicated that learning motivation had a negative moderating role; and if the coefficient was not significant, it indicated that learning motivation had no moderating effect.

$$\begin{aligned} EF_{uy} = {} & \beta_0 + \beta_1 Z_{uy} + \beta_2 Z_{uy} * APR_{uy} + \beta_3 APR_{uy} + \beta_4 BL_{uy} \\ & + \sum IN + \sum YE + \gamma_{uy} \end{aligned} \tag{10}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Main regression test results

Variables	(1) Innovative Literacy	(2) Innovative Literacy	(3) Innovative Literacy	(4) Innovative Literacy	(5) Innovative Literacy	(6) Innovative Literacy
Information acquisition ability	0.012**		0.013***	0.011**		0.015**
	(6.35)		(8.34)	(2.48)		(2.68)
Information application ability		0.009***	0.013**		0.009**	0.011**
		(5.89)	(7.56)		(2.85)	(2.75)
Gender	0.002***	0.001***	0.002***	0.002***	0.001*	0.002***
	(6.78)	(4.65)	(5.78)	(2.54)	(2.18)	(2.35)
Major	0.054***	0.058***	0.052***	0.054***	0.055***	0.056***
	(7.23)	(6.58)	(6.84)	(18.12)	(18.29)	(21.58)
Learning time	0.022***	0.025***	0.023***	0.022***	0.028***	0.021***
	(11.28)	(15.24)	(11.22)	(3.89)	(3.84)	(3.18)
Teaching quality	0.045***	0.044***	0.043***	0.042***	0.048***	0.041***
	(16.58)	(15.92)	(18.48)	(6.46)	(6.52)	(6.79)
Practical experience	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(9.46)	(9.58)	(9.13)	(6.89)	(7.42)	(6.33)
Extracurricular activities	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(11.25)	(11.89)	(11.54)	(11.24)	(9.53)	(9.61)
Grade	0.049***	0.048***	0.047***	0.050***	0.049***	0.051***
	(21.29)	(21.38)	(21.14)	(3.52)	(3.64)	(3.47)
Information technology	Control	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control	Control
_cons	0.097***	0.096***	0.089***	0.095***	0.087***	0.098***
	(12.58)	(9.65)	(11.35)	(7.85)	(11.23)	(8.69)
N	13.268	13.268	13.268	13.268	13.268	13.268
$Adj.R^2$	0.346	0.365	0.342	0.343	0.344	0.354

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

Columns 1 and 2 of Table 1 show the regression results. The clustering and robust standard errors of the model were adjusted at the information technology level, and columns 4 and 5 show the adjusted regression results. After information acquisition and application skills were inserted into the same model, the entire sample was regressed, and clustering and robust standard errors were adjusted, the results of which are shown in columns 3 and 6 of Table 1. The following conclusions were drawn based on the data in the table.

The regression results of all models showed that information acquisition ability had a significant positive impact on innovative literacy. The coefficient of information acquisition ability was positive and significant in three models, namely the model with no adjustment of clustering and robust standard errors, such as columns 1 and 2; the model with such an adjustment, such as columns 4 and 5; and the model considering both information acquisition and application abilities, such as columns 3 and 6, supporting hypothesis 1 that information acquisition ability has a positive impact on innovative literacy.

Similarly, regardless of which models were used, the coefficient of information application ability was positive and significant, indicating that the ability had a significant positive impact on innovative literacy, supporting hypothesis 2 that information application ability has a positive impact on innovative literacy.

After accounting for control variables such as gender, major, learning time, teaching quality, practical experience, extracurricular activities, and grade, the influence of information acquisition and application abilities on innovation literacy remained significant and positive. This indicates that the impact of these two factors on innovative literacy was influenced by these control variables, supporting hypotheses 3 and 4 concerning the moderating role. These control variables had a significant impact on innovative literacy as well. The coefficients of gender, major, learning time, teaching quality, practical experience, extracurricular activities, and grade were all positive, indicating that these factors had a positive impact on innovative literacy.

Column 1 in Table 2 shows the empirical results of information acquisition ability and innovative literacy of regression; column 2 shows the empirical results of information acquisition and processing abilities of regression; column 3 shows the regression results; column 4 shows the empirical results of information application ability and innovative literacy; column 5 shows the regression results of information application and processing abilities; and column 6 shows the regression results of putting innovative literacy, information application ability, and the mediating variable (information processing ability) into the same regression model. The following conclusions were drawn based on the data in the table.

In columns 1 and 3, information acquisition ability had a significant positive impact on innovative literacy, which confirmed the previous hypothesis 1 that information acquisition ability has a positive impact on innovative literacy. In column 2, information acquisition ability had a significant positive impact on information processing ability as well, indicating that information acquisition ability enhanced information processing ability.

In columns 4 and 6, information application ability had a significant positive impact on innovative literacy, confirming the previous hypothesis 2 that information application ability has a positive impact on innovative literacy. In column 5, information application ability had a significant positive impact on information processing ability, indicating that information application ability enhanced information processing ability. In column 6, when information acquisition, application, and processing skills were considered simultaneously, all three had a significant positive impact on innovation competence. This suggests that information processing skills play a partially mediating role in the impact of information acquisition and application skills on innovation competence, thereby confirming hypotheses 3 and 4.

Table 2. Mediating effect test of information processing ability

Variables	(1) Innovative Literacy	(2) Information Processing Ability	(3) Innovative Literacy	(4) Innovative Literacy	(5) Information Processing Ability	(6) Innovative Literacy
Information acquisition ability	0.011***	0.175**	0.012***			
	(6.33)	(2.64)	(6.58)			
Information application ability				0.009***	0.364***	0.008**8
				(5.89)	(6.23)	(5.58)
Gender			0.002***			0.002***
			(7.23)			(7.43)
Major	0.002***	0.175***	0.002***	0.001***	0.168***	0.001***
	(6.78)	(12.68)	(5.88)	(4.68)	(13.58)	(3.87)
Learning time	0.022***	1.099***	0.018***	0.025***	1.321***	0.022***
	(7.22)	(62.35)	(3.25)	(6.98)	(58.65)	(2.39)
Teaching quality	0.022***	1.259***	0.018***	0.021***	1.235***	0.024***
	(11.21)	(13.28)	(9.35)	(11.36)	(16.34)	(9.58)
Practical experience	0.042***	0.158*	0.048***	0.046***	0.123	0.042***
	(18.29)	(1.826)	(17.19)	(17.46)	(1.35)	(17.36)
Extracurricular activities	0.006***	0.008	0.006***	0.006***	0.007	0.006***
	(9.87)	(0.31)	(9.67)	(9.79)	(0.27)	(9.58)
Grade	0.005***	0.126***	0.005***	0.005***	0.114***	0.005***
	(11.26)	(6.25)	(11.98)	(11.25)	(5.88)	(11.62)
Information technology	0.048***	7.125***	0.061***	0.047***	7.121***	0.057***
	(21.35)	(81.36)	(23.23)	(23.19)	(81.36)	(23.18)
Year	Control	Control	Control	Control	Control	Control
_cons						
N	0.095***	2.654***	0.094***	0.078***	2.134***	0.072***
	(12.68)	(7.34)	(12.46)	(9.22)	(6.87)	(8.96)
Adj.R^2	14312	14312	14312	14312	14312	14312
Information acquisition ability	0.353	0.611	0.367	0.353	0.625	0.353

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

In summary, the data in the table supported all hypotheses that information acquisition and application abilities have a positive impact on innovative literacy, while information processing ability played a partial mediating role in this impact.

The mediating effect test aimed to investigate whether the learning environment and motivation regulated the impact of information acquisition and application abilities on innovative literacy. This study tested these hypotheses by analyzing the significance of the interaction term between the information acquisition ability of the learning environment and learning motivation, as well as the significance of the interaction term between the information application ability of the learning environment and learning motivation. Assuming hypothesis 4a is true, it was observed that the interaction term of learning environment and information acquisition ability was significant in predicting innovative literacy, which indicates that the quality of the learning environment regulated the impact of information acquisition ability on innovative literacy. Assuming hypothesis 4b is true, the interaction term of learning motivation and information acquisition ability was significant in predicting innovative literacy, indicating that the level of learning motivation regulated the impact of information acquisition ability on innovative literacy. Assuming hypothesis 5a is true, the interaction term of learning environment and information application ability was significant in predicting innovative literacy, indicating that the quality of the learning environment regulated the impact of information application ability on innovative literacy. Assuming hypothesis 5b is true, the interaction term of learning motivation and information application ability was significant in predicting innovative literacy, indicating that the level of learning motivation regulated the impact of information application ability on innovative literacy.

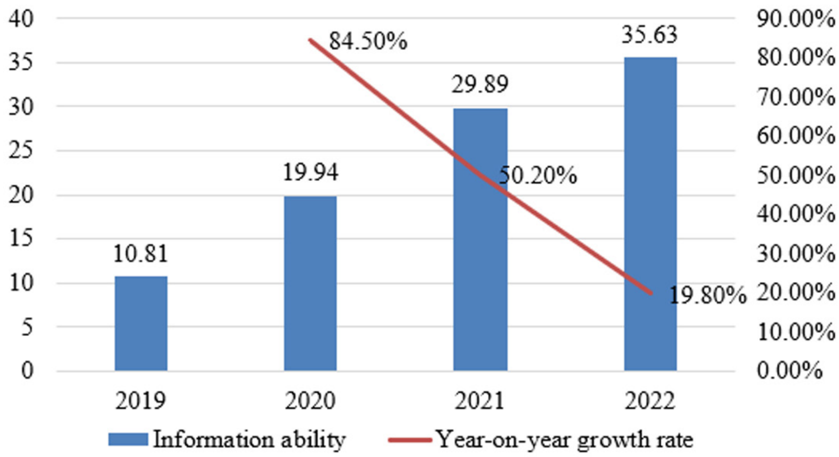

Fig. 1. Information ability of digital talents in universities

Figure 1 shows the changes in the information ability of university digital talents from 2019 to 2022. It is clear that the information ability continues to improve, and the growth rate is relatively fast during this period. Several key trends can be revealed from this data. In four years, the information ability of digital talents in universities significantly improved, from 10.81 in 2019 to 35.63 in 2022. Although information ability continues to grow, the growth rate decreases each year. The year-on-year growth rate of information ability reached 84.5% from 2019 to 2020, but decreased to 50.2% in 2021 and further decreased to 19.8% in 2022. The decreasing growth rate year after year may indicate that the improvement of information ability may become saturated in the future, especially in digital talent cultivation in universities. In summary, these data indicate that universities have made significant progress in cultivating the information ability of digital talents, but the growth rate is slowing. In the future, universities should consider how to continuously improve educational methods to further enhance the informational abilities of students. At the same time, the saturation trend should be prevented in order to continuously cultivate high-quality digital talents for society.

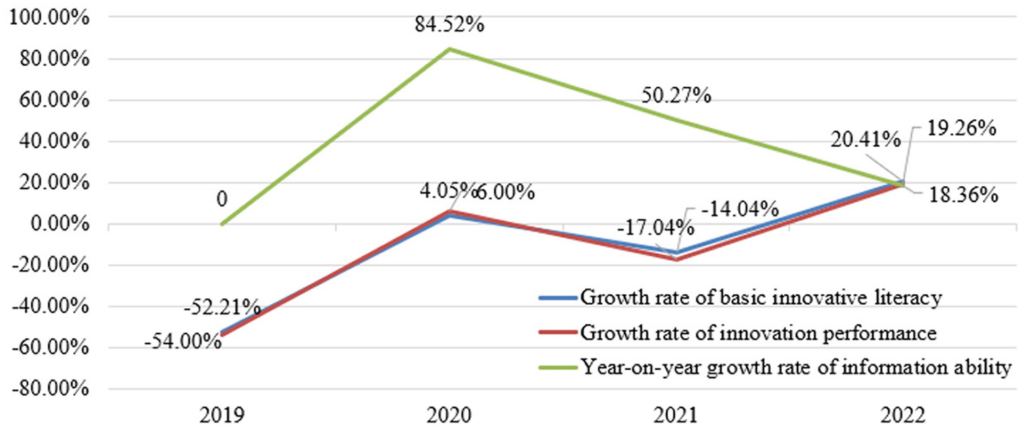

Fig. 2. Changes in innovative literacy growth ability of university digital talents

Figure 2 shows the changes in the growth rates of basic innovative literacy and innovation performance and the year-on-year growth rate of the information ability of university digital talents from 2019 to 2022. Several key trends can be found based on the data. Over the past four years, the growth rate of basic innovative literacy and innovation performance has fluctuated, with both positive and negative growth, indicating that the innovative literacy and innovation performance of university digital talents may be influenced by multiple factors, including policies, teaching methods, technological changes, etc. Although the year-on-year growth rate decreases, information ability is still improving, which may have a positive impact on innovative literacy and innovation performance. It can be seen that in years when the growth rate of information ability increases (e.g., 2020 and 2022), the growth rate of basic innovative literacy and innovation performance also shows an upward trend, suggesting that improving information ability helps improve innovative literacy and innovation performance. Based on the above analysis, it was concluded that although there was some fluctuation in the basic innovative literacy and innovation performance of university digital talents, continuous improvement of information ability may help improve the performance of these two aspects. Universities should focus on improving the information ability of students, which may help them improve their innovative literacy and innovation performance. At the same time, for the volatility of innovative literacy and innovation performance, universities should further analyze other factors affecting the volatility of these two indexes in order to better enhance the innovation ability of students.

5 CONCLUSION

This research aimed to study the relationship between information ability and innovative digital literacy in universities, and analyze various factors affecting this relationship. Based on several key hypotheses, this study constructed separate mediating and moderating effect models and deeply analyzed the impact of factors such as information processing ability, learning environment, and motivation.

The research results showed that there was a significant positive relationship between information acquisition and application abilities and innovative literacy, and information processing ability played a significant mediating role in this process, indicating that digital talents in universities improved their information processing ability by effectively acquiring and applying information, thereby enhancing their innovative literacy.

The research results further showed that the learning environment and motivation had a significant moderating effect on the relationship between information acquisition, application abilities, and innovative literacy. A good learning environment and high learning motivation enhanced the positive impact of information acquisition and application abilities on innovative literacy.

In addition, the comparative analysis revealed differences in the innovative literacy performance of university digital talents in different dimensions of information ability. Most talents had moderate performance in information acquisition, processing, application, and innovation abilities, but their percentage of good performance in information application and innovation abilities was relatively low.

Overall, this study revealed a close relationship between information ability and innovative literacy of digital talents in universities, as well as the importance of learning environment and motivation in influencing this relationship, providing an important theoretical basis and practical guidance for universities to cultivate innovative digital talents. Other factors that may affect this relationship can be further explored in future studies, thereby promoting the effectiveness and efficiency of digital talent cultivation in universities.

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7 REFERENCES

[1] A. Badawood, "Supply chain management in higher education: A conceptual model within COVID-19 outbreak, building a proposed conceptual model," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 13, pp. 201–211, 2021. https://doi.org/10.3991/ijet.v16i13.21845

[2] G. Hu, "Research on new generation of information technology innovation promoting the reform of standardization activities," *Journal of Physics: Conference Series*, vol. 2026, no. 1, p. 012009, 2021. https://doi.org/10.1088/1742-6596/2026/1/012009

[3] S. M. Chege, D. Wang, and S. L. Suntu, "Impact of information technology innovation on firm performance in Kenya," *Information Technology for Development*, vol. 26, no. 2, pp. 316–345, 2020. https://doi.org/10.1080/02681102.2019.1573717

[4] Z. Ren, "Training path for talents engaged in agricultural product supply chain management and the assessment of their training quality," *International Journal of Emerging Technologies in Learning*, vol. 17, no. 20, pp. 118–133, 2022. https://doi.org/10.3991/ijet.v17i20.34523

[5] J. L. Carlo, J. Gaskin, K. Lyytinen, and G. M. Rose, "Early vs. late adoption of radical information technology innovations across software development organizations: An extension of the disruptive information technology innovation model," *Information Systems Journal*, vol. 24, no. 6, pp. 537–569, 2014. https://doi.org/10.1111/isj.12039

[6] B. Pang, T. Chen, and M. Dai, "Analysis on the development of visual communication design under the innovation of information technology," in *International Conference on Applications and Techniques in Cyber Intelligence*, Fuyang, China, pp. 535–543, 2022. https://doi.org/10.1007/978-3-031-29097-8_63

[7] J. Wei and C. Wang, "A differential game analysis on green technology innovation in a supply chain with information sharing of dynamic demand," *Kybernetes*, vol. 52, no. 1, pp. 362–400, 2021. https://doi.org/10.1108/K-04-2021-0296

[8] S. Makhni, A. Atreja, A. Sheon, B. Van Winkle, J. Sharp, and N. Carpenter, "The broken health information technology innovation pipeline: A perspective from the NODE health consortium," *Digital Biomarkers*, vol. 1, no. 1, pp. 64–72, 2017. https://doi.org/10.1159/000479017

[9] T. Gao, "Research on the construction of innovation literacy index system of higher vocational students based on big data," in *2nd International Conference on Big Data, Information and Computer Network (BDICN)*, Xishuangbanna, China, pp. 13–16, 2023. https://doi.org/10.1109/BDICN58493.2023.00010

[10] L. Meng, Q. Xin, and Q. Fan, "Application of artificial intelligence in pre-school education professional talent training in the era of big data," in *International Conference on E-Learning, E-Education, and Online Training*, Harbin, China, pp. 654–670, 2022. https://doi.org/10.1007/978-3-031-21164-5_50

[11] L. Yi and S. Yan, "Construction and index analysis of whole chain linkage talent training system based on fuzzy AHP model," *Journal of Sensors*, vol. 2022, pp. 1–12, 2022. https://doi.org/10.1155/2022/7106274

[12] Y. Huang, "The optimization algorithm for the cultivation of medical literacy in the era of smart media," in *International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, Ballar, India, pp. 1–5, 2023. https://doi.org/10.1109/ICDCECE57866.2023.10150740

[13] Y. Shi, F. Sun, H. Zuo, and F. Peng, "Analysis of learning behavior characteristics and prediction of learning effect for improving college students' information literacy based on machine learning," *IEEE Access*, vol. 11, pp. 50447–50461, 2023. https://doi.org/10.1109/ACCESS.2023.3278370

[14] Z. Chen, S. Wang, D. Jiang, and X. Tang, "Research on information transmission capability evaluation of information processing system based on fuzzy mathematics comprehensive evaluation method," in *IEEE 10th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, Chongqing, China, pp. 44–48, 2022. https://doi.org/10.1109/ITAIC54216.2022.9836628

[15] C. Han, P. Jian, W. Xiong, and J. Fu, "Evaluation of joint information environment service capability of space-based network information system based on ANP-fuzzy comprehensive evaluation method," in *IEEE 10th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, Chongqing, China, pp. 1324–1331, 2022. https://doi.org/10.1109/ITAIC54216.2022.9836948

[16] J. Liu, S. Wu, T. Hu, and J. Liu, "Evaluation method of multi-domain system information sharing capability," in *Proceedings of 10th China Conference on Command and Control*. C2 2022. Lecture Notes in Electrical Engineering, Springer, Singapore, vol. 949, 2022. https://doi.org/10.1007/978-981-19-6052-9_60

[17] N. Songkram, N. Songkram, S. Chootongchai, and T. Samanakupt, "Developing students' learning and innovation skills using the virtual smart classroom," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 4, pp. 34–51, 2021. https://doi.org/10.3991/ijet.v16i04.15221

[18] P. Chen, "Information literacy cultivation and course informationization construction of university management course," in *International Conference on Applications and Techniques in Cyber Intelligence: Applications and Techniques in Cyber Intelligence (ATCI 2020)*, Advances in Intelligent Systems and Computing, Springer, Cham Fuyang, China, vol. 1244, pp. 16–21, 2021. https://doi.org/10.1007/978-3-030-53980-1_3

[19] M. Wang, "Analyzing the influence of college aesthetic education teaching on college students' innovation ability and artistic literacy based on decision tree classification model," *Mobile Information Systems*, vol. 2022, no. 9587049, 2022. https://doi.org/10.1155/2022/9587049

[20] X. Li and Q. Xing, "Design of an intelligent sensor teaching experiment system and measurement of student innovation literacy," *Journal of Sensors*, vol. 2022, no. 6128884, 2022. https://doi.org/10.1155/2022/6128884

[21] X. Zhao, "The research on the cultivation of innovation capabilities supported by information technology: A case study of 'soil mechanics and foundation engineering' course," in *International Conference on Information Science and Education (ICISE-IE)*, Sanya, China, pp. 435–438, 2020. https://doi.org/10.1109/ICISE51755.2020.00099

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