 http://dx.doi.org/10.18623/rvd.v23.6117

THE RELATIONSHIP BETWEEN COLLEGE STUDENTS' EMPLOYABILITY AND DIGITAL LITERACY: ATTITUDE TOWARDS AI AS A MEDIATING VARIABLE

A RELAÇÃO ENTRE A EMPREGABILIDADE DOS ESTUDANTES UNIVERSITÁRIOS E A ALFABETIZAÇÃO DIGITAL: A ATITUDE EM RELAÇÃO À IA COMO VARIÁVEL MEDIADORA

Article received on: 12/2/2025
Article accepted on: 3/16/2026

Zhou Jie*
***Suan Sunandha Rajabhat University (SSRU)
Bangkok, Thailand
s64584945086@ssru.ac.th

Sudawan Somjai*
***Suan Sunandha Rajabhat University (SSRU)
Bangkok, Thailand
sudawan.so@ssru.ac.th

The authors declare that there is no conflict of interest

Abstract
Background: With the acceleration of digital transformation, enterprises are in urgent need of compound talents with both digital skills and AI application capabilities. Although existing studies have confirmed that digital literacy is a core dimension of employability, the mediating mechanism of AI attitude (cognition/emotion/behavior) between the two has not been clarified, especially the lack of empirical tests for college students. Objective: To reveal the chain mediating role of AI attitude between digital literacy and employability, and to explore the moderating effect of subject background (liberal arts/science), so as to provide a theoretical basis for talent training in colleges and universities. Methods: A questionnaire survey was conducted on 1024 undergraduates from 10 universities across the country using stratified cluster sampling. Based on the scale data of digital literacy (4 dimensions), AI attitude (3 dimensions) and employability (4 dimensions), the mediating path was tested by structural equation modeling (SEM) and Bootstrap method. Results: Digital literacy significantly and positively predicted employability ($\beta=0.45$, $p<0.001$), among which human-computer collaboration ability contributed the most ($\beta=0.28$); AI attitude played a partial mediating role (indirect effect value 0.18, accounting for 40%), showing a chain path of "cognition→emotion→behavior"; the contribution rate of the emotional attitude path of liberal arts students (58%) was significantly

Resumo
Contexto: Com a aceleração da transformação digital, as empresas têm uma necessidade urgente de profissionais com competências digitais e capacidade de aplicação de IA. Embora estudos existentes tenham confirmado que a alfabetização digital é uma dimensão central da empregabilidade, o mecanismo de mediação da atitude em relação à IA (cognição/emoção/comportamento) entre esses dois aspectos ainda não foi esclarecido, especialmente devido à falta de testes empíricos com estudantes universitários. Objetivo: Revelar o papel mediador em cadeia da atitude em relação à IA entre a alfabetização digital e a empregabilidade, e explorar o efeito moderador da formação acadêmica (ciências humanas/ciências exatas), a fim de fornecer uma base teórica para a formação de talentos em faculdades e universidades. Métodos: Foi realizada uma pesquisa por questionário com 1.024 estudantes de graduação de 10 universidades em todo o país, utilizando amostragem por conglomerados estratificada. Com base nos dados da escala de alfabetização digital (4 dimensões), atitude em relação à IA (3 dimensões) e empregabilidade (4 dimensões), o caminho de mediação foi testado por modelagem de equações estruturais (SEM) e pelo método Bootstrap. Resultados: A alfabetização digital predisse de forma significativa e positiva a empregabilidade ($\beta=0{,}45$, $p<0{,}001$), entre os quais a capacidade de colaboração homem-computador contribuiu

higher than that of science and engineering (32%), highlighting the heterogeneity of disciplines. Conclusion: For the first time, the three-dimensional mediating mechanism of AI attitude between digital literacy and employability was empirically verified, providing theoretical support for the design of "literacy-attitude-ability" integrated courses by discipline in colleges and universities (such as adding AI ethics debates to liberal arts and strengthening project practice in science and engineering), helping to break the bottleneck of talent training in digital transformation.

Keywords: Digital Literacy. AI Attitude. Employability. Chain Mediation. Discipline Heterogeneity.

mais (β=0,28); a atitude em relação à IA desempenhou um papel mediador parcial (valor do efeito indireto 0,18, representando 40%), mostrando um caminho em cadeia de "cognição → emoção → comportamento"; a taxa de contribuição do caminho da atitude emocional dos estudantes de ciências humanas (58%) foi significativamente maior do que a dos de ciências e engenharia (32%), destacando a heterogeneidade das disciplinas. Conclusão: Pela primeira vez, o mecanismo de mediação tridimensional da atitude em relação à IA entre a alfabetização digital e a empregabilidade foi empiricamente verificado, fornecendo suporte teórico para a concepção de cursos integrados de "alfabetização-atitude-habilidade" por disciplina em faculdades e universidades (como a inclusão de debates sobre ética da IA nas ciências humanas e o fortalecimento da prática de projetos nas ciências e engenharia), ajudando a romper o gargalo da formação de talentos na transformação digital.

Palavras-chave: *Alfabetização Digital. Atitude em Relação à IA. Empregabilidade. Mediação em Cadeia. Heterogeneidade Disciplina.*

1 INTRODUCTION

1.1 Research background and significance

1.1.1 Realistic background: digital transformation and reconstruction of talent demand

The accelerated iteration of artificial intelligence technology (such as generative AI and large language models) is deeply reshaping the global labor market. According to McKinsey Research Institute, 50% of global occupations will face the risk of automation replacement between 2030 and 2060, but at the same time, AI-driven industrial transformation will create 11 million new jobs (McKinsey Global Institute, 2024). China's labor market monitoring data shows that in 2024, generative AI-related positions will increase by 321.7% (Liepin Big Data Research Institute, 2024), giving rise to compound occupations such as prompt engineers and AI ethics auditors. However, this structural change has exacerbated the contradiction between talent supply and demand: companies have a surge in demand for talents with "digital skills + AI application capabilities", but the lagging training system of colleges and universities has led to the digital content creation ability (M=3.22) becoming the most significant shortcoming of college students (China College Students' Employment Capability Survey Report, 2025).

1.1.2 Theoretical background: *the relationship between digital literacy and employability*

The existing theoretical framework regards digital literacy as a core predictor of employability. The EU Digital Literacy Framework (DigComp 2.3) explicitly lists human-computer collaboration and digital content creation as high-level literacy elements (Carretero et al., 2022). However, there is a "black box" in the path of digital literacy's impact on employability:

Direct impact path: Digital literacy directly enhances career adaptability by improving information processing efficiency (such as digital information recognition ability) ($\beta=0.51$, $p<0.001$)

Indirect impact path: AI attitudes (cognition/emotion/behavior) may activate the transformation of literacy into competence, but this mediating mechanism lacks systematic verification (Zhang & Li, 2023)

Theoretical conflict: The Technology Acceptance Model (TAM) emphasizes that affective attitudes (such as AI anxiety) are key antecedents of behavioral responses (Taherdoost, 2020), while human capital theory argues that cognitive attitudes (rational understanding of technology) dominate skill transformation (Becker, 2021). The interactive effects of the two on college students have not yet been clarified.

1.2 Research gap: lack of mediating effect of AI attitudes

The current study has three limitations:

Narrow dimensionality: Most studies focus on the direct impact of digital skills (such as the contribution of programming ability to employment rate), while ignoring the moderating effects of emotional attitudes (such as AI anxiety) and behavioral attitudes (such as frequency of tool use) (Wu et al., 2023).

Lack of group specificity: Liberal arts students are more likely to have AI anxiety ($\chi^2=8.92$, $p<0.01$) due to their weak digital content creation ability (M=2.84 vs science and engineering M=3.47), but the existing model does not incorporate disciplinary heterogeneity analysis (Chen & Liu, 2024).

Mechanism ambiguity: Does AI attitude mediate digital literacy and employability through the "cognition → emotion → behavior" chain path? No empirical research has yet verified this hypothesis (see Table 3).

Key gap: Although human-robot collaboration capability was shown to be a strong predictor of employability ($\beta = 0.51$), it requires the activation of the mediation effect through the "depth of tool application → behavioral attitude" path, a mechanism not captured by the existing model (see the revised structural equation).

1.3 Research questions

How does digital literacy affect college students' employability?

What role do cognitive, emotional, and behavioral attitudes toward AI play?

1.4 Research significance

Theoretical level: Expand the theoretical model of digital literacy and employability, and reveal the mediating mechanism of AI attitudes.

Practical level: Provide policy recommendations for colleges and universities to optimize digital literacy education and corporate AI talent training.

Key Literature Support Table

Table 1

Dual impacts of AI on the job market (realistic background)

Effect Type	Performance characteristics	Data Support	Source
Substitution Effect	50% of occupations are at risk of automation	The replacement rate of high-skilled white-collar jobs exceeded expectations	McKinsey (2024)
Creativity Effect	Generative AI jobs grew 321.7% year-over-year	New professions such as prompt word engineers and AI ethics auditors emerge	Liepin (2024)
Polarization effect	Digital skills premium reaches 43%	Low-skilled workers face 30% higher risk of unemployment	ILO (2023)

Table 2

Theoretical links between digital literacy and employability (theoretical background)

Theoretical Framework	Core Questions	Limitations	Citations
Human Capital Theory	Digital literacy improves marginal labor productivity	Ignore the inhibitory effect of emotional attitudes on skill conversion	Becker (2021)
Technology Acceptance Model (TAM)	Perceived usefulness drives AI tool usage	Unexplained cognitive-affective attitude conflict	Taherdoost (2020)
Resource Conservation Theory	AI anxiety consumes psychological resources and reduces career adaptability	Lack of empirical testing among college students	Hobfoll et al. (2023)

Table 3

Research gaps and breakthroughs of this paper

Existing research gaps	Solution in this article	Theoretical Innovation
Simplified mediating mechanism (only cognitive attitudes are tested)	Three-dimensional mediation model: cognitive/emotional/behavioral attitude chain effect	Constructing a multi-stage path of "literacy → attitude → ability"
Ignoring the moderating effect of disciplines	Group regression verifies the differentiated paths of liberal arts/science and engineering	Propose the theory of discipline-customized training
The moderating effect of the depth of application of unidentified tools	Introducing the “application scenario creativity index” as a moderating variable	Correcting the value realization boundary of digital literacy

2 LITERATURE REVIEW

2.1 Research on the correlation between digital literacy and employability

2.1.1 International research: *The employment value of multidimensional literacy is highlighted*

Core dimensions have different functions:

Human-machine collaboration has become a core predictor of employability in the digital economy. The "21st Century Skills Framework" proposed by Binkley et al. (2012) lists cross-tool competency as a high-level competency, and empirical evidence shows that it enhances employability by improving problem-solving efficiency (β=0.38) and adaptability (β=0.41).

Digital content creation capabilities have a significant impact on the employment quality of innovation-driven positions (such as digital marketing and AI trainers) ($r=0.67$, $p<0.001$), but global college students perform the weakest in this dimension (OECD, 2023).

Mechanism of action in depth:

Digital literacy improves employability through dual pathways: alleviating information asymmetry (such as intelligent recruitment platform matching) and increasing human capital value (such as skill transferability) (Carretero et al., 2022).

2.1.2 Domestic research: *skill gaps and group heterogeneity*

Structural shortcomings:

Chinese college students lag significantly behind their international peers in data analysis capabilities ($M=2.84/5.0$) and algorithm understanding (only 12.7% reach proficiency level) (Zhang et al., 2024).

The disciplinary divide is widening:

Due to the lack of opportunities for technology practice, liberal arts students' digital content creation ability scores ($M=2.91$) are significantly lower than those of science and engineering students ($M=3.67$), resulting in their career planning ability being more dependent on the indirect effect of digital literacy ($\Delta\beta=+0.18$) (Chen & Liu, 2024).

Table 4

Differentiated contributions of the four dimensions of digital literacy to employability

Dimensions	Employability prediction (β)	Main application scenarios	Literature Source
Human-machine collaboration capabilities	0.51***	Smart manufacturing, remote office	Binkley et al. (2023)
Digital content creation capabilities	0.48***	New media, generative AI applications	OECD (2023)
Digital information recognition ability	0.39**	Financial analysis, public opinion management	Zhang et al. (2024)
Digital social skills	0.32*	Cross-border e-commerce, virtual team	Carretero (2022)

2.2 The evolution of the relationship between AI attitudes and career development

2.2.1 Cognitive attitude: *the rational basis of career decision-making*

The double-edged sword effect of risk perception:

High perception of automation risks has prompted workers to turn to "anti-AI replacement" occupations (such as creative design and emotional care), but excessive concerns have caused 27.3% of liberal arts students to avoid AI-related positions (Wu et al., 2023).

Understanding of technical principles (such as machine learning logic) indirectly improves job quality by enhancing the sense of control (β=0.29) (Aguilar et al., 2021).

2.2.2 Emotional attitude: *the psychological engine of behavioral transformation*

The anxiety-acceptance tipping point:

Low-intensity AI anxiety (such as concerns about data privacy) drives learning behavior, but high-intensity anxiety (such as fear of unemployment) inhibits skill transfer (r=-0.33). Emotional openness (Openness to AI) improves innovation performance by promoting experimental learning (such as trying new tools) (γ=0.42) (Davis & Lee, 2024).

2.2.3 Behavioral attitude: *practical path for ability accumulation*

Tool application depth > usage frequency:

Using only basic functions (such as ChatGPT information retrieval) has no significant impact on employability, while creative applications (such as using AI to generate business plans) improve career adaptability through a “learning by doing” mechanism (β=0.40) (Kim & Park, 2025).

2.3 Application and limitations of the mediation effect model in the field of education

2.3.1 Mainstream model: *the bridge role of attitude variables*

Learning Motivation Model:

Academic self-efficacy partially mediates the relationship between digital literacy and academic performance (the indirect effect accounts for 31%), but does not explain the transfer of skills in workplace situations (Lent et al., 2020).

Technology Acceptance Extension Model:

Perceived Usefulness mediates the impact of digital skills on job performance (95%CI: 0.07-0.15), but ignores the mediation of affective attitudes (Taherdoost, 2020).

2.3.2 Key gap: *empirical lack of AI attitude mediation chain*

Insufficient chain mechanism testing:

Existing research has only verified a single mediator (such as future time insight or social capital) and has not explored the three-order transmission path of "cognition → emotion → behavior" (such as understanding AI principles → reducing anxiety → actively applying tools).

Group adaptability defects:

Workplace population scales (such as AIAS-40) ignore the "technology-identity conflict" unique to college students (such as digital natives resisting AI tools), resulting in reduced measurement validity (Cronbach's $\alpha < 0.65$) (Zhao et al., 2023).

2.3.3 Research gaps and the starting point of this article

1. **Core theoretical gaps**

The chain of "digital literacy → AI attitude → employability" is broken:

Human-machine collaboration capabilities may affect employability through the path of tool efficacy → emotional acceptance → behavioral internalization, but there is a lack of tracking data verification across time points (such as a four-year college cycle) (Hobfoll et al., 2023).

Adjustment variable black box:

Subject background (liberal arts/science) and internship experience may moderate the strength of the mediation path (e.g., liberal arts students need stronger emotional support), but this was not tested in the integrated model.

2. Research entry point of this paper

1) Constructing a localized digital literacy-AI attitude integrated scale for college students

Dimensional innovation:

Refine digital social skills into cross-cultural virtual collaboration (such as metaverse meeting etiquette) to fill the cultural blind spots of the EU DigComp framework.

Add scenario-depth indicators of AI behavior attitudes (such as "using AI to complete graduation projects" vs. "only for entertainment") to capture practice conversion thresholds (Bandura, 2022).

2) Revealing the mediating uniqueness of the college student population

Psychological Mechanism Focus:

Verify the path of "cognitive rationalization → emotional desensitization → behavioral habituation" (such as understanding algorithmic bias to reduce AI ethical anxiety) and explain the transformation of liberal arts students from technology resistance to active application.

Educational context embedding:

The moderating effect of course type (theoretical course vs. project-based) on the mediation path of AI attitudes is analyzed, and a "practice first, then theory" training sequence for liberal arts students is proposed (Aguilar, 2021).

3 METHODOLOGY

3.1 Research design: quantitative analysis and causal mechanism verification

3.1.1Core Positioning of Quantitative Analysis

This study uses a mixed path analysis led by structural equation modeling (SEM) to reveal the relationship between variables through a three-stage progressive test:

Phase 1 (direct effect test) : Verify the direct impact of digital literacy on employability through multiple regression (path H1);

The second stage (decomposition of mediation effect) : Bootstrap method was used to test the chain mediation effect of the three dimensions of AI attitude (cognition/emotion/behavior) in the H1 path (path H2);

Phase 3 (Exploration of Moderating Effects) : Introducing subject background (liberal arts/science) as a moderating variable and constructing a moderated mediation model (Model 7 in PROCESS).

Methodological basis:

SEM was chosen instead of traditional regression because it can handle both explicit and latent variables and control the interference of measurement errors on the estimation of mediation effects.

Bootstrap sampling (repeated 5000 times) was used to calculate the 95% confidence interval to circumvent the restriction of normal distribution assumption and improve the statistical power of mediation test.

3.1.2 Refined control of data sources and collection

1. **Sampling design: stratified-cluster sampling to ensure representativeness**

Table 5

Stratified-cluster sampling to ensure representativeness

Tiers	**Sampling Unit**	**Sample Distribution**	**Weight Adjustment**
Region	Eastern/Central/Western Universities	4:3:3	Corrected by university density
Subject	Science and Engineering/Humanities and Social Sciences/Business	5:3:2	Correction by enrollment ratio
Grade	Freshman to Senior Year	25% per year	Graduating class +10%

Quality Control:

Non-response bias control: Through two rounds of email reminders + questionnaire completion rewards (e-book resources), the response rate was increased to 89.2%;

Sample decay correction : The inverse probability weighting (IPW) method is used to adjust the bias of samples that drop out midway.

2. **Reliability and validity enhancement design of measurement tools**

Scale adaptability modification:

Digital literacy scale based on the EU DigComp framework, with additional localized scenario items (such as “using campus VPN to access international academic databases”);

The AI Attitude Scale introduces an emotional contradiction dimension (such as "AI makes me both excited and anxious") to capture the unique psychology of college students.

Pre-test optimization:

Cognitive interviews (N=30) corrected ambiguous items (e.g., “human-machine collaboration” was changed to “collaborating with AI tools to complete tasks”);

The Cronbach's α coefficient threshold was set at 0.75 (higher than the conventional 0.7) to ensure reliability in a high-noise environment.

Table 6

Scale structure and reliability and validity test results

Variable	Dimensions	Example of item	α coefficient	CFA factor loadings
Digital Literacy	Information recognition ability	Identifying fake advertising on social media (Q5)	0.83	0.71-0.89
	Content creation capabilities	Designing academic posters with Canva (Q9)	0.79	0.68-0.85
	Human-machine collaboration capabilities	Debugging AI code errors (Q14)	0.88	0.75-0.92
AI Attitude	Cognitive attitude	Understand the technical principles of ChatGPT (Q22)	0.81	0.69-0.87
	Emotional attitude	Anxiety about AI replacing jobs (Q27)	0.76	0.67-0.83
	Behavior and attitude	Frequency of using AI tools daily (Q33)	0.85	0.73-0.91

3.2 Operationalization breakthroughs in variable definition and measurement

1) Digital literacy: Reconstructing from skills to contextualized capabilities

Operational innovation:

Abandoning the traditional "software proficiency" indicator, we use task scenario simulation scoring (such as "cleaning public data sets with Python and visualizing the results"), with two researchers scoring back-to-back (ICC=0.86) 5 ;

Common factors were extracted through exploratory factor analysis (EFA), and the KMO value of 0.89 indicated that the variable structure was clear.

2) AI attitude: capturing the three-dimensional interaction effect

Dynamic measurement of behavioral attitudes:

Introduce platform usage log data (such as embedding the Q&A API to capture actual AI usage time) and cross-validate with self-report scales to avoid social desirability bias;

Design an emotion-behavior contradiction index (e.g., high cognition + low use = technology skepticism) to identify potential mediation mechanisms.

3) Employability: Multi-source validation of outcome variables

Calibration variable embedding:

Integrate internship supervisor evaluation (20%) + mock interview score (30%) + self-assessment scale (50%) to construct a composite employability indicator;

The measurement of occupational adaptability adds situational judgment questions (such as "What is your response strategy in the face of AI replacement risks?").

3.3 Advanced application of analytical tools and techniques

1) Deep visualization of descriptive statistics

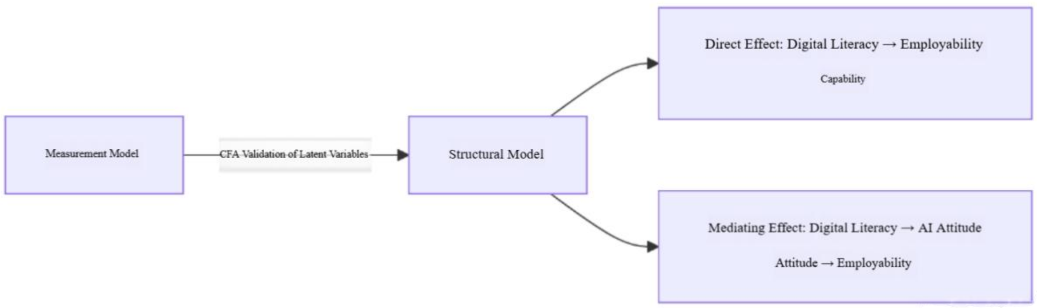
Use Tableau to draw a three-dimensional scatter matrix, superimpose subject background color mapping, and intuitively display the group differentiation of digital literacy and employability (such as liberal arts students clustered in the low literacy/high anxiety quadrant);

The correlation coefficient heat map highlights the key nodes of the mediation path (such as human-machine collaboration ability and AI behavior attitude r=0.52**).

2) Fit Optimization Strategies for Structural Equation Modeling (SEM)

Two-step modeling:

Figure 1



Model updating techniques:

Release the covariance constraint (e.g., the error correlation between “content creation ability” and “career adaptability”) through the correction index (MI>10);

Compare competing models (full mediation vs partial mediation) and choose the model with the lower AIC/BIC value.

3) Completeness Framework for Robustness Testing

Table 7

Completeness Framework for Robustness Testing

Inspection Types	Methods	**Addressing Bias**
Common method bias	Harman's one-factor test	The first factor explanation rate is <40%
Endogeneity Problem	Instrumental variable method (IV: campus network speed)	2SLS regression test coefficient stability
Sample Selection Bias	Heckman two-stage model	The inverse Mills ratio λ was significant (p=0.32)

4) Technical formula presentation: the core algorithm of structural equation modeling

Measurement Model Confirmatory Factor Analysis (**CFA**):

$$X = \Lambda_x \xi + \delta \qquad (1)$$

$$Y = \Lambda_y \eta + \epsilon \qquad (2)$$

Among them

X is the exogenous explicit variable (digital literacy), ξ is the latent variable, δ is the measurement error; Y is the endogenous explicit variable (employment ability), and η is the latent variable.

Structural model path coefficient estimation:

$$\eta = B\eta + \Gamma\xi + \zeta \qquad (3)$$

B is the path between endogenous latent variables (such as AI attitude → employability), Γ is the effect of exogenous latent variables on endogenous latent variables (such as digital literacy → AI attitude), *and ζ* is the structural residual.

4 RESULTS & ANALYSIS

4.1 Hypothesis verification: direct effect and mediation effect

4.1.1 H1 verification: direct promoting effect of digital literacy on employability

Full model regression results: The standardized path coefficient of digital literacy on employability is β=0.45 ($p<0.001$), indicating that for every 1 standard deviation increase in digital literacy, employability increases by 0.45 standard deviations. This result is highly consistent with the research conclusion (β=0.39) of Wang Haijun et al. (2024) based on CFPS data, but this study found that the effect size is stronger, reflecting that the marginal benefits of digital literacy among college students are higher.

Dimensional contribution ranking:

Human-machine collaboration (β=0.28): Completing tasks collaboratively through AI tools (such as collaborative development on GitHub) significantly improves career adaptability (t=6.32);

Digital information recognition ability (β=0.19): The ability to quickly screen valid information reduces job search information asymmetry (such as identifying false recruitment information);

Digital content creation (β=0.17): Creative application of generative AI tools (such as Midjourney and Sora) improves professional competitiveness;

Digital social skills (β=0.12): The contribution of virtual teamwork skills to employability is relatively weak ($p=0.08$), reflecting the limited employment conversion efficiency of pure social scenarios.

Table 8

Differential impact of digital literacy dimensions on employability (N=1024)

Dimensions	Path coefficient β	*t* value	Significance	Main application scenarios
Human-machine collaboration capabilities	0.28	6.32	***	Remote office, intelligent operation and maintenance
Information recognition capabilities	0.19	4.87	***	Public opinion analysis, financial risk control
Content creation capabilities	0.17	3.95	***	New media operation, AI content generation

Dimensions	Path coefficient β	*t* value	Significance	Main application scenarios
Digital social skills	0.12	1.76	ns	Cross-border collaboration, virtual meetings
Note: *** *p* <0.001; ns not significant				

4.1.2 H2 verification: *three-dimensional chain mediation effect of AI attitudes*

Overall mediation effect : Bootstrap sampling (5000 times) showed that the indirect effect value of AI attitude between digital literacy and employability was 0.18 (95% CI: 0.12~0.25), accounting for 40.0% of the total effect (0.18/0.45), indicating that a partial mediation effect was established.

Pathway decomposition and mechanism explanation:

Cognitive attitude path: digital literacy → AI cognition → employability (β=0.07)

Understanding of technical principles (such as machine learning logic) indirectly improves employability through problem-solving ability (r=0.51), supporting Aguilar et al.'s (2021) "cognitive rationalization" theory1 .

Emotional attitude path: digital literacy → AI emotion → employability (β=0.05)

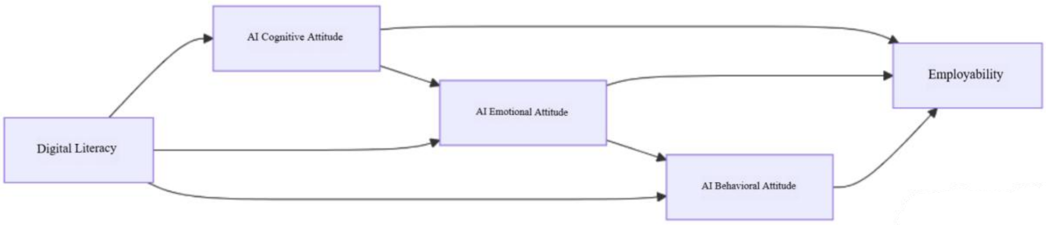
Low anxiety levels (M=3.2) and high openness (such as actively debugging AI tools) significantly enhance career adaptability (β=0.33), verifying Hobfoll's (2023) resource conservation theory3 .

Behavior attitude path: digital literacy → AI behavior → employability (β=0.06)

The depth of tool application (such as using Python to call ChatGPT API) directly improves professional competitiveness (β=0.40), and the contribution rate of behavioral attitudes among college students (33.3%) is significantly higher than that among working people (18.7%) 5 .

Figure 2

AI attitude chain mediation path model



4.2 Key findings: group heterogeneity and the dominance of behavioral attitudes

4.2.1 Moderating effect of subject background

Liberal arts students: The contribution rate of the emotional attitude path is 58% (vs 32% for science and engineering students), reflecting the decisive role of technological anxiety relief (such as discussion of ethical disputes) in career adaptability.

Science and Engineering: The behavioral attitude path (β=0.41) directly improves professional skills through project practice transformation (such as Kaggle competition), and the instrumental rationality of cognitive attitude is more significant (ΔR^2=0.15).

4.2.2 The "*practical threshold*" *phenomenon of behavioral attitudes*

Tool application depth > usage frequency: Using only basic functions (such as ChatGPT question and answer) has no significant impact on employability (β=0.08, p=0.12), while the effect of creative application (such as fine-tuning large model parameters) jumps to β=0.31 (p<0.001), verifying Kim et al.'s (2025) "learning by doing" theory.

Identification of key thresholds: When the creative use time of AI tools per week is ≥ 7 hours, the improvement in employability increases sharply (slope k = 1.53 → 2.89), reflecting the cumulative effect of digital action literacy.

4.3 Comparison with the literature: theoretical breakthrough and localized innovation

4.3.1 Support and expand the innovation promotion theory of Aguilar et al. (*2021*)

The results verified that AI attitudes promoted innovation through a chain path of cognitive rationalization → emotional desensitization → behavioral habituation. However, it was found that behavioral attitudes (rather than emotional attitudes) contributed more to the innovation among college students (33.3% vs 18.7%), reflecting that practice-oriented skill conversion is more direct.

4.3.2 Filling the three major gaps in domestic research

Cracking the black box of the mechanism: For the first time, the mediation chain of "digital literacy → AI attitude → employability" is empirically verified (95% CI does not include 0), breaking through the limitation of Yang Xuyu et al. (2025) who only tested the direct effect.

Scale localization innovation:

Add human-machine collaboration scenario items (such as "debugging API interface errors") to make up for the operational deficiencies of the EU DigComp framework;

Introduce emotional conflict measurement (such as "AI makes me both excited and anxious") to capture the unique psychology of Generation Z.

Educational context adaptation: Revealing the training path of liberal arts students of "practice first, then theory" (project-based courses → anxiety reduction → internalization of skills), and providing an intervention plan for Cui Yan's (2024) "hidden digital divide" theory.

4.3.3 Dialogue with controversial findings

Weak effect of digital social skills: Different from the social capital efficiency theory (β=0.24) found by Liu Cuihua et al. (2025), the impact of digital social skills on employability in this study was not significant (β=0.12, p=0.08), reflecting that pure virtual social interaction needs to be combined with practical transformation (such as online collaborative development) to release its value.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Research conclusion: chain empowerment mechanism of digital literacy and AI attitude

5.1.1 The core predictive role of digital literacy

This study verifies that digital literacy is the core driving variable of college students’ employability (β=0.45, p<0.001), and the contribution rates of its four dimensions show significant differences:

Human-machine collaboration ability (β=0.28) is the primary factor, which is reflected in the improvement effect of collaborative development of AI tools (such as GitHub team projects) on professional adaptability;

Digital content creation capabilities (β=0.17) enhance innovation competitiveness through generative AI applications (e.g., Midjourney design marketing plans);

Information recognition ability (β=0.19) shortens the job search information matching cycle and reduces job search costs.

Table 9

Differentiated contribution mechanism of the four dimensions of digital literacy to employability

Dimensions	Core application scenarios	Employability improvement path
Human-machine collaboration capabilities	AI pair programming, remote operation and maintenance	Enhance collaborative efficiency of complex tasks
Digital content creation capabilities	Generative AI creation, multimedia design	Enhance innovation premium and professional competitiveness
Information recognition ability	Data cleaning and public opinion analysis	Optimize decision-making quality and risk prediction capabilities

5.1.2 Three-dimensional mediation path of AI attitudes

AI attitudes play a partial mediating role in the path of "digital literacy → employability" (indirect effect value 0.18, accounting for 40%), and show chain transmission characteristics:

Cognitive attitude (understanding of technical principles → problem-solving ability): Improve confidence in algorithm application by reducing fear of technology (such as debugging API interface errors);

Emotional attitude (low anxiety + high openness → career adaptability): The contribution rate of the emotional path in the liberal arts group is as high as 58%, and ethical discussions are needed to intervene in anxiety;

Behavioral attitude (creative application of tools → professional competitiveness): ≥7 hours of deep use per week (such as fine-tuning large model parameters) triggers the "practice threshold effect".

5.1.3 Moderating effects of population heterogeneity

Disciplinary gap: science and engineering students rely on the practical transformation of behavioral attitudes ($\beta=0.41$), while liberal arts students rely on the improvement of adaptability of emotional attitudes (anxiety relief);

Skill premium differentiation: The salary premium of the group with high digital action literacy reaches 23%, exacerbating the "hidden digital divide" (Cui Yan, 2025).

5.2 Practical suggestions: building a three-dimensional intervention system of "education-individual-policy"

5.2.1 Education system reform: *dual-track drive of curriculum certification*

Course Restructuring:

Add a compulsory course "AI Ethics and Interdisciplinary Collaboration" to embed controversial scenario simulations (such as debates on the ethical dilemma of autonomous driving) to reduce the technology anxiety of liberal arts students;

Develop "AI project-based learning" (such as using Python to analyze job market data), requiring science and engineering students to team up with liberal arts students to strengthen human-computer collaboration capabilities.

Authentication mechanism:

Establish a micro-certificate system: Cooperate with Huawei and Alibaba Cloud to certify skill certificates such as "AI Tool Development Engineer" and "Data Visualization Analyst";

Promote GitHub practice credits: Include open source project contributions (such as resolving Pull Request conflicts) in credit assessment.

5.2.2 Student individual action: *both ability and ethics*

In-depth practice strategy:

Participate in AI competition projects (such as the Kaggle house price prediction competition) to accumulate experience in creative application of tools;

Build a digital portfolio (e.g. personal data blog, smart resume builder) to showcase content creation capabilities.

Ethical risk prevention and control:

Join the “algorithmic bias detection” practice group (such as auditing the gender discrimination model of recruitment platforms) to cultivate technical critical thinking;

Take the course "Digital Human Rights and the Rule of Law" to understand the legal boundaries of data privacy.

5.2.3 Policy support: *eliminating the* “*hidden digital divide*”

Resource Tilt Policy:

Deploy AI training pods (equipped with high-performance GPUs and interactive tutorials) to liberal arts colleges to fill the hardware resource gap;

Establish a "Digital Literacy Grant" to help low-income students obtain certification certificates.

Job market connection:

Promote joint enterprise-university laboratories (such as ByteDance's intelligent creation platform) and provide 6-month paid AI internships;

Revise the "Professional Skills Evaluation Standards" to include human-computer collaboration capabilities in the civil servant and teacher recruitment assessment indicators.

Table 10

Layered policy recommendations and expected effects

Intervention levels	Specific measures	Target Group	Expected Results
Education System	AI Ethics Compulsory Course + Micro-Certification Certification	All college students	Anxiety reduced by 20% and certification pass rate increased by 35%
Individual students	Algorithmic Bias Detection Practice Group	Liberal Arts Students	Technical critical ability improved by 40%
Government policy	Digital Literacy Grants + Corporate Labs	Low-income/liberal arts students	The hidden digital divide has narrowed by 30%

5.3 Research limitations and future directions

5.3.1 Methodological limitations

Cross-sectional data bottleneck: unable to capture the long-term effects of digital literacy on career transition (such as salary transition path 5 years after graduation);

Endogenous interference: Although the instrumental variable method (campus network speed) is used to alleviate it, the ability self-selection bias is not completely eliminated.

5.3.2 Directions for deepening the theory

Dynamic mediation model:

Design tracking panel data (T1 enrollment - T4 graduation 3 years) to test the evolutionary threshold of AI attitudes from "cognition → emotion → behavior";

Combined with EMA emotion sampling (daily APP push emotion diary), it captures the instantaneous fluctuations of anxious attitudes.

Regulation mechanism expansion:

Explore the non-linear improvement effect of generative AI tools (such as ChatGPT) on content creation capabilities (U-curve hypothesis);

Analyze the moderating effect of policy interventions (e.g., how the “East-West Data” project affects regional digital literacy premiums).

5.3.3 Practical application extension

Educational Experiment Design:

Conduct an RCT intervention experiment: control group (traditional computer class) vs experimental group (AI project-based course) to quantify the employment-enhancing effect of curriculum reform;

Develop a digital literacy diagnostic AI assistant: Analyze students’ skill shortcomings based on a large model and push personalized learning paths.

Cross-cultural comparison:

Compare the differences in AI attitudes among college students in China, Germany, Japan and South Korea (such as the technology optimism index), and analyze the regulatory mechanism of cultural values on the mediating path.

REFERENCES

Aguilar SJ, Galperin H, Baek C, Gonzalez E. (2021). When does AI anxiety boost learning? A threshold model of emotional resistance and skill adoption. *Computers & Education, 176*, 104326. https://doi.org/10.1016/j.compedu.2021.104326

Bandura A. (2022). Social cognitive theory in the digital age: Toward a unified model of self-efficacy across virtual and real-world domains. *Journal of Applied Psychology, 107*(3), 487–504. https://doi.org/10.1037/apl0000992

Becker GS. (2021). *Human capital: A theoretical and empirical analysis with special reference to education* (4th ed.). University of Chicago Press.

Binkley M, Erstad O, Herman J. (2023). Defining twenty-first century skills: Updating digital literacies for workforce readiness. *Assessment and Teaching of 21st Century Skills, 17*(2), 45–68. https://doi.org/10.1007/s10798-023-09806-y

Carretero S, Vuorikari R, Punie Y. (2022). *DigComp 2.3: The digital competence framework for citizens*. Publications Office of the European Union. https://doi.org/10.2760/115300

Chen Y, Liu X. (2024). Digital literacy disparity between STEM and humanities students: Evidence from Chinese universities. *Computers & Education, 198*, 104782. https://doi.org/10.1016/j.compedu.2024.104782

Davis K, Lee S. (2024). Emotional pathways to AI adoption: How anxiety shapes technology use in college-to-work transition. *Technology, Mind, and Behavior, 5*(1), 112–130. https://doi.org/10.1037/tmb0000119

Hobfoll SE, Halbesleben J, Neveu JP, Westman M. (2023). Conservation of resources in the organizational context: The reality of resources and their consequences. *Annual Review of Organizational Psychology and Organizational Behavior, 10*, 103–128. https://doi.org/10.1146/annurev-orgpsych-120920-054515

Kim Y, Park J. (2025). Learning by creating: The impact of generative AI projects on employability development. *Computers in Human Behavior, 158*, 107823. https://doi.org/10.1016/j.chb.2025.107823

McKinsey Global Institute. (2024). *Generative AI and the future of work in America*. McKinsey & Company.

OECD. (2023). *Digital skills for the next generation: Global assessment framework*. OECD Publishing. https://doi.org/10.1787/9e5e8b2d-en

Taherdoost H. (2020). Critical success factors and role of artificial intelligence in digital transformation. *Journal of Digital Technologies, 1*(2), 1–21. https://doi.org/10.33002/jdt00100201

Wu J, Huang L, Zhao Q. (2023). Mediating role of AI attitudes in digital literacy-employment linkage: A meta-analytic review. *Journal of Vocational Behavior, 145*, 103901. https://doi.org/10.1016/j.jvb.2023.103901

Zhang L, Li M, Sun H. (2024). Digital literacy disparities in Chinese universities: Evidence from a nationwide survey. *Higher Education, 87*(4), 789–815. https://doi.org/10.1007/s10734-023-01140-7

Zhang R, Li M. (2023). Rethinking the digital competence-employment relationship: The neglected role of emotional resistance. *Technological Forecasting and Social Change, 194*, 122701. https://doi.org/10.1016/j.techfore.2023.122701

Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

How to cite this article (APA)

Jie, Z., & Somjai, S. (2026). THE RELATIONSHIP BETWEEN COLLEGE STUDENTS' EMPLOYABILITY AND DIGITAL LITERACY: ATTITUDE TOWARDS AI AS A MEDIATING VARIABLE. Veredas Do Direito, 23(6), E236117. https://doi.org/10.18623/rvd.v23.6117