

The Relationship between Student Learning Readiness to Use AI on Technological Competence for Employability Skills Development in Chinese Universities

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Abstract

The rapid advancement of technology has revolutionised how businesses operate, which has in turn also transformed the skills and competencies that are desired among the young workforces. This research aims to explore how the integration of Artificial Intelligence (AI) into higher education curricula offers a transformative opportunity to enhance students' employability skills and better prepare them for the future workforce. This quantitative research proceeds with the integration of the constructivist learning theory, which has helped in the identification of key independent variables: "Cognitive Strategies", "E-learning Experience", "Student Perception" and "Student Engagement", along with the mediating impact of "Technology Proficiency". The interrelationship of these variables is explored with the development of certain hypotheses that highlight the cumulative impact on "Students' Employability Skills". The primary data is collected based on a quantitative research design in this study, and 380 students from Shanghai University are selected. The IBM SPSS software can be used for the analysis of data in this study. The outcomes of the research validate the assumptions made in this study, further highlighting that the constructs chosen are relevant and play a significant role in enhancing the employability skills of the students.

Keywords: Learning Environment, Interactive Simulations, Gamification, Real Time Feedback, E-Learning Experience

Introduction

Research Background

Artificial intelligence (AI) is making significant contributions to the transformation of the higher educational landscape (Bucea-Manea-Toniş et al. 2022). The focus on the overall enhancement of the AI literacy framework is associated with the improvement of the learning quality. It can be impactful for the cognitive knowledge development of students.

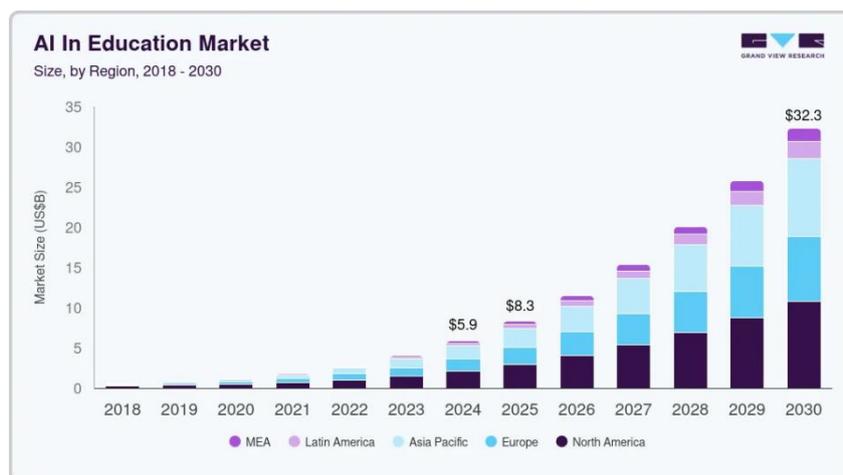


Fig. 1 The Graph of Integrating AI in the Education Sector

(Source: grandviewresearch.com, 2024)

It is reported by *Grand View Research* that the size of the worldwide AI in the education sector was assessed at *USD 5.88 billion* in 2024 and is expected to increase at a *compound annual growth rate (CAGR)* of *31.2%* from 2025 to 2030, reaching *USD 32.27 billion*. It is motivated by the growing need for individualised educational experiences (Musarrat Saber Nipun et al., 2023). Therefore, it can be stated based on the findings gained from previous research works, AI-integration in curriculum development plays a significant role and it is considered supportive to enhance the future career of students. The research can be impactful to delve more in the various aspects of it.

Research Issues

The foremost goal of education is to foster the talents of students and to provide them with a holistic learning experience. In this process, the integration of technological innovations such as Artificial Intelligence (AI), Big Data, Machine Learning, and others transcends the conventional paradigm of one-size-fits-all in traditional education systems (Bhutoria, 2022). Despite this, in the Chinese educational sector, a lack of readiness among the students in AI adoption can be observed which not only undermines technological competence among the students but also hinders the employability skills among the students. Though various initiatives are taken to enhance the AI-assisted personalised learning and usage of the technology in curriculum designing, issues like inefficient measures for securing information are observed (Bhutoria 2022).

However, Kong, Cheung & Zhang (2023) have expressed that the cognitive dimension focuses on teaching core AI concepts, especially machine learning and deep learning, and how these can be applied to analyse and interpret real-world situations. Understanding these concepts is crucial for developing AI literacy, given their significant impact on society. However, a lack of AI literacy among students often stems from limited exposure to these foundational concepts, which hinders their ability to critically engage with AI technologies and understand their societal impact. Hence, the outcome of the study will be effective in further providing more integrated insight about the problem or can give ideas about ways to manage it. Based on the purpose of this study, some research questions are also developed that are below-

RQ1: What is the significant impact of cognitive strategies on students' employability skills in Chinese higher education?

RQ2: What is the significant effect of e-learning experience on students' employability skills in Chinese higher education?

RQ3: What is the significant influence of student perception on students' employability skills in Chinese higher education?

RQ4: What is the significant impact of student engagement on students' employability skills in Chinese higher education?

RQ5: What is the significant mediating impact of technological proficiency on students' employability skills in Chinese higher education?

Significance of the Study

The study may have significant practical significance because the ideas that will be obtained from the research can be supportive for policymakers in terms of implementing necessary steps to enhance the AI-integrated curriculum that can contribute to improving the skills of students. In addition, the educational institution can be able to enhance its ideas in terms of integrating or considering factors like incorporating cognitive strategies or considering student perception before policy development to prevent security-related issues and providing smooth AI-based learning facilities. In addition, the study may have some theoretical implications in terms of adding value to the existing literature about AI-integration and education. In addition to this, the significance of this research is also associated with informing strategies to bridge the gap between AI education and real-world job requirements, ensuring that students are better prepared for future careers.

Literature Review

Theoretical Framework

Constructivist Learning Theory (CLT) renders critical thinking, problem-solving, and self-directed learning highly relevant in AI-integrated higher education. When used for AI-based learning environments, CLT encourages the students to interact with digital tools, apply cognitive strategies and develop real-world competencies required in the modern job market (M. Givi Efgivia et al. 2021). The criticality of CLT has an impact on cognitive strategies, e-learning experience, student perception, and student engagement in line with the most important variables in impacting students' employability skills (Marougkas et al. 2023). The association with the relationship between student learning preparedness to use AI, technological competence, and the development of employability skills is associated with the Constructivist Learning Theory (CLT). This causes the perception that they have to be positive, and as such, their involvement in technological skills acquisition makes them more efficient (Rohm, Stefl, & Ward, 2021). Therefore, there is a direct effect of the CLT and AI integration on the development of the employability skills where students grow adaptable, skilled and work-ready graduates.

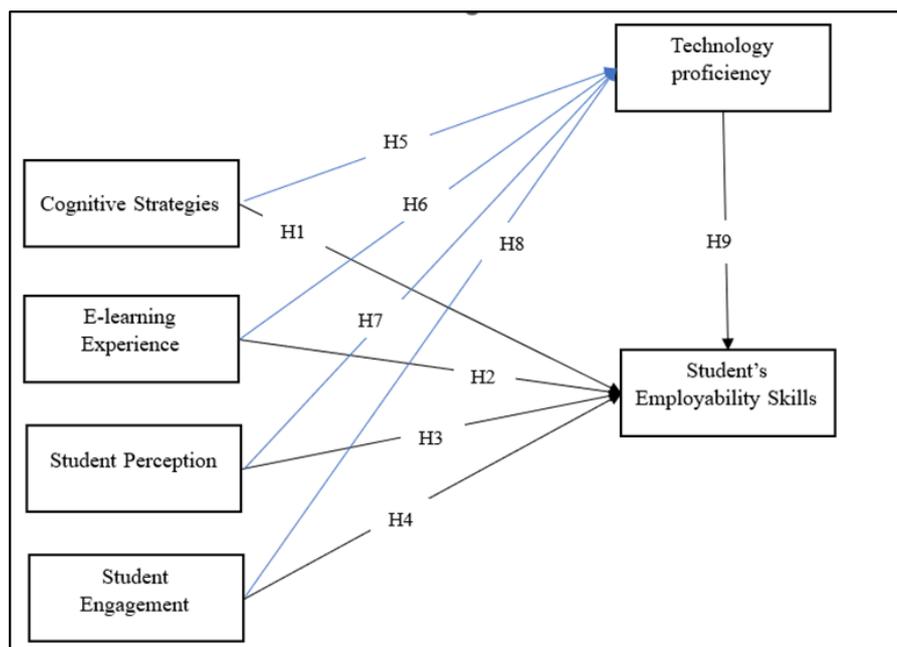


Fig. 1 Framework of the Research

In the context of Chinese universities, the integration of artificial intelligence (AI) in education is rapidly increasing to enhance students' abilities. It helps to adopt effective cognitive strategies to determine how efficiently they can learn and apply technological knowledge. El-Sakran (2023) indicated that the employability skills like decision making, adaptability, and analytical reasoning are increasingly demanded by employers in the digital economy. Thus, it is strongly justified that students who utilise effective cognitive strategies prefer to demonstrate high levels of creativity, technological competence, and professional adaptability for improving employability skills.

H1: Cognitive strategies have a significant impact on Students' employability skills

According to Martinez-Argüelles, Plana-Era & Fitó-Bertran (2023), in the modern workplace, employees are expected to be proficient in digital tools, collaborative platforms, and problem-solving in technology-rich environments. Moreover, Raza, Qazi & Umer (2020) supported that e-Learning platforms enable adaptive learning paths, real-time feedback, and exposure to industry-relevant technologies. By fostering technology engagement, collaborative problem solving, and self-discipline through e-Learning, the Chinese universities can enhance the readiness of the students for a professional environment. This increasingly depends on digital solutions.

H2: E-learning experience has a significant impact on Students' employability skills

Student perception is an important factor in shaping employability skills, mainly within the context of AI-driven learning in Chinese universities. The positive perception highlights self-directed adaptability, learning, and problem-solving abilities as the main employability skills demanded in the labour market (Hazaymeh, 2021). Consequently, the negative perceptions like scepticism, fear of AI replacement, or lack of trust in its outcomes may hinder effective skill acquisition and reduce employability prospects. Alegre (2023) suggested that in higher education, the belief of the students in the use of digital and AI-based systems can increase motivation to apply and learn knowledge in a real-world context.

H3: Student perception has a significant impact on Students' employability skills

According to El-Sakran (2023), the engagement reflects the degree of effort, participation, and involvement students exhibit in academic and skill-oriented activities. Previous studies indicated that students who demonstrate higher engagement in technologically mediated learning environments acquire transferable competencies (Kudiyarbekovna 2023). Thus, the hypothesis shows engagement as the central driver of developing employability skills. It underscores the notion that, beyond the availability of AI tools, students must actively immerse themselves in learning activities to harness the potential of AI for professional growth.

H4: Student engagement has a significant impact on Students' employability skills

According to Fogel (2022), technology proficiency means technical skills and the capacity to understand and integrate tools for professional and academic purposes. Moreover, Shanmugasundaram & Tamilarasu (2023) claimed that cognitive strategies have enhanced adaptability as the main factor for technology adoption in the dynamic learning environment. Previous studies and research suggested that high-order cognitive strategies, like reflective thinking, can strengthen the outcome of technology learning by promoting deeper understanding (Gerlich, 2025). This is because they empower students to leverage technology effectively for academic success and future employability.

H5: Cognitive strategies have a significant impact on Technology Proficiency

Al-smadi, Abugabah & Smadi (2022) claimed that the frequency, quality, and diversity of e-Learning experience contribute significantly to the comfort level of students maintaining adaptability with the digital platform. According to Akporokah (2022), e-learning fosters digital literacy by integrating multimedia resources, cloud-based collaboration, and self-paced learning, which enhances students' technical confidence. Additionally, exposure to diverse e-learning platforms improves adaptability, problem-solving, and innovative thinking to align with global employability standards.

H6: E-learning experiences have a significant impact on Technology Proficiency

In the context of Chinese universities, AI is increasingly integrated into educational practices. Ubaidillah et al. (2020) indicated that such perception acts as a psychological gateway to technological competence. Thus, students' beliefs, attitudes, and perceived usefulness of AI technologies significantly enhance their ability to acquire technological proficiency. It also determines how well they evolve workplace and digital academic demands.

H7: Student perception has a significant impact on Technology Proficiency

Kusumo et al. (2024) claimed that active engagement through participation in interactive learning platforms, AI-driven projects, and collaborative tasks provides students with hands-on experience, practical competence, and deeper insights. Furthermore, Godsk & Møller (2024) stated that engagement can extend beyond classroom participation to involve self-initiated activities such as online learning, coding practice, or AI-based simulations. All these experiences provide opportunities for strengthening problem-solving, technological, and adaptability fluency. Therefore, higher student engagement fosters stronger technological proficiency.

H8: Student engagement has a significant impact on Technology Proficiency

According to Đorđević et al. (2025), proficiency equips students with practical competencies where digital communication thinking skills in adaptability are significant. Moreover, Scheuring & Thompson (2024) highlight proficiency to promote creativity and innovation as it allows the graduate students to contribute to the organisational digital transformation. Thus, Technology proficiency is referred to as technical requirements and the foundation for employability skills to ensure students thrive in AI-augmented professional environments.

H9: Technology proficiency has a significant impact on Students' employability skills

Despite increased research on the integration of AI in higher education, greater knowledge will be contributed to furthering the link between AI integration and enhancing University students' employability skills. In addition, technology proficiency as a gap bridging in AI education and workforce readiness is not explored.

Methodology

Positivist philosophy and deductive approach will be included in this method to collect information, following the quantitative design. Based on the requirements of the study, the use of a quantitative design may help to adopt an appropriate structure to develop the entire study and the steps of data collection while ensuring reliability and validity. The use of quantitative design will help in collecting the numerical data to develop answers according to the research questions and identify research problems (Taherdoost 2021). It will help in proving the impact of independent variables on the dependent variables by highlighting their relationship with each other. The descriptive research design would be considered as a suitable design for the quantitative study; this design allows for analysing underlying trends and patterns in the data through frequencies and trends.

Data collected through surveys can be easily analysed with the help of this research design. It will also assist in selecting the appropriate test to validate the developed hypothesis, ensuring a positive outcome and leading to more reliable conclusions (Singh 2023). It also involves the detailed process of analysing the collected data related to the learning readiness of students to use artificial intelligence in the higher education curriculum, on the employability skills of the students. As per the views of Hossan, Dato'Mansor & Jaharuddin (2023), populations help define the limits of the research and provide an idea about the surroundings and context, as well as the opportunity to focus on specific areas within a predetermined scope.

The study is conducted considering the employability improvement of the students and the consideration of AI integration in their curriculum. Hence, university students are selected as the respondents for the study in terms of gaining relevant ideas about the factors that impact their technological privacy or skills. Therefore, the total university student population from Shanghai University is selected in this study (apply.studyinchina.edu.cn, 2023). The number of full-time students in the university is 40000, hence, a random sampling method should be employed alongside the five-point Likert scale to get a desirable number of respondents from the population.

N	S	N	S	N	S	N	S	N	S
10	10	100	80	280	162	800	260	2800	338
15	14	110	86	290	165	850	265	3000	341
20	19	120	92	300	169	900	269	3500	246
25	24	130	97	320	175	950	274	4000	351
30	26	140	103	340	181	1000	276	4500	351
35	32	150	108	360	186	1100	285	5000	357
40	36	160	113	380	181	1200	291	6000	361
45	40	180	118	400	196	1300	297	7000	364
50	44	190	123	420	201	1400	302	8000	367
55	48	200	127	440	205	1500	306	9000	368
60	52	210	132	460	210	1600	310	10000	373
65	56	220	136	480	214	1700	313	15000	375
70	59	230	140	500	217	1800	317	20000	377
75	63	240	144	550	225	1900	320	30000	379
80	66	250	148	600	234	2000	322	40000	380
85	70	260	152	650	242	2200	327	50000	381
90	73	270	155	700	248	2400	331	75000	382
95	76	270	159	750	256	2600	335	100000	384

Note: "N" is Population Size
"S" is Sample Size.

Fig. 2 The Krejcie and Morgan Table
(Source: Muchai & Ng'asike, 2021)

It can be stated, based on the table above, that the suitable sample size for a 40000 population is 380 (Muchai & Ng'asike, 2021). Hence, surveying with 380 university students is expected to be a feasible number of respondents in this case. Moreover, the simple random sampling method is considered the simplest and most commonly employed method of selecting a sample, in which the sample is selected unit by unit, with equal probability of selection for each unit at each draw. It can be supportive to conduct the data collection in a bias-free manner, and each of the respondents should get an equal chance to be included in the sample size.

According to Taherdoost (2021), data collection is the most critical stage in research and can overshadow the quality of results by decreasing the possible errors that may occur during a research project. Therefore, this research is to be carried out in compliance with a primary data collection method, as the information gathered in this process is specifically tailored to address the research questions and ensures the data is directly aligned with the study's objectives. The research can be conducted with the help of quantitative data analysis methods. It is identified from the previous sections that primary data can be gained through a survey questionnaire, hence, a quantitative data analysis may be suitable to analyse these data.

Two main approaches of data analysis would be performed using the IBM SPSS software. The primary advantage of this software is associated with its user-friendly Graphical User Interface (GUI), which makes it easy to learn and use. This includes the descriptive and inferential analysis. Under the descriptive research design, measures of central tendency would be implemented to calculate the mean and standard deviation of the data (Tumiran, 2023). In the context of this current research, the research instrument is a self-administered survey questionnaire. The questions developed in this study comprise closed-ended questions on the variables selected for the research model. The questions are to be responded to with five options: 1) strongly disagree, 2) disagree, 3) neutral, 4) agree, and 5)

strongly agree. The participants were asked to rate their answers and responses according to the developed questions and topic.

This research may test the reliability of the variables employed in it through Cronbach's Alpha technique. The technique evaluates the degree of internal reliability of the items employed in the questionnaire. The validity testing can also be undertaken to ensure that the variables used measure what they are supposed to measure. Pearson Correlation analysis can test the relationship among the variables. **"The Personal Data Protection Act, 2021"** can be followed in the study to uphold the integrity and security of the respondents (dlapiperdataprotection.com. 2025). Additionally, the students have been informed that participation in the survey is entirely voluntary, and they are free to withdraw from the process at any point without facing any consequences or being required to explain.

Results of Analysis

Sample Characteristics and Data Distribution

The demographic data entailed in this study highlights the viewpoints expressed by the students in Shanghai University in China. It can be observed from the demographic data of the respondents that the majority of the pupils, which is 170 individuals, belong within the age group of 18 to 20 years accounting for 44.7% of the respondents.

Table 1

Profile of factors characterizing the demographic of the sample

		Count	Column N %
Age	18-20 years	170	44.7%
	21-23 years	148	38.9%
	Above 23 years	62	16.3%
Gender	Male	181	47.6%
	Female	199	52.4%
Ethnicity	Han	46	12.1%
	Shanghainese	106	27.9%
	Miao	96	25.3%
	Hui	99	26.1%
	Others	33	8.7%

Based on the data it can be comprehended that there are 181 male and 199 female respondents which makes up 47.6% and 52.4% of the respondents. It can be observed from the abovementioned table that this research has encompassed respondents from varied backgrounds wherein the largest ethnic group is Shanghainese (n=106) with 27.9% representation. The diverse cultural and regional backgrounds of the pupils might impart a significant impact on the views and opinions alongside impacting their learning readiness and technological competence in using AI.

Measurement of Model Evaluation

Reliability and Validity

The value of Cronbach's Alpha is 0.970, while the Alpha based on standard eyes items is 0.971 including a total of 36 items. The Cronbach's Alpha is a widely used indicator of

internal consistency, where values above 0.70 are generally considered acceptable, above 0.80 are good, and values exceeding 0.90 indicate excellent reliability.

Table 2
Cronbach's Alpha

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.970	.971	36

Validity Analysis

The correlation value between CS and SES is .892, while CS and EE have correlation of .847, and with SP is .837. It indicates that SES have a higher level of impact on student's employability skills.. Moreover, it is also strongly associated with technology proficiency of students. The correlation between CS and TP is .703, while the correlation between CS and SE is .803. This sig value is slightly lower than others.EE also has the highest correlation value with SES that is .933. It refers to the perfect and positive relationship between e-learning experiences and student's employability skills.

Table 3
Distinguishing Validity- Pearson's Correlation Coefficient Test

Correlations							
		CS	EE	SP	SE	TP	SES
CS	Pearson Correlation	1	.847**	.837**	.803**	.703**	.892**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	380	380	380	380	380	380
EE	Pearson Correlation	.847**	1	.917**	.904**	.767**	.933**
	Sig. (2-tailed)	.000		.000	.000	.000	.000
	N	380	380	380	380	380	380
SP	Pearson Correlation	.837**	.917**	1	.876**	.737**	.915**
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	380	380	380	380	380	380
SE	Pearson Correlation	.803**	.904**	.876**	1	.727**	.895**
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	380	380	380	380	380	380
TP	Pearson Correlation	.703**	.767**	.737**	.727**	1	.800**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	380	380	380	380	380	380
SES	Pearson Correlation	.892**	.933**	.915**	.895**	.800**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	380	380	380	380	380	380

** . Correlation is significant at the 0.01 level (2-tailed).

The SE and SP also have the highest correlation of .933 that indicates a nearly perfect positive relationship with each other. The EE also has a strong and positive correlation SE at .904 and SP at .917. It refers to that e-learning experience has a significant relationship with student engagement and student perception. On the other hand, the correlation between EE and TP is .767 that is quite lower and also lower than the other correlation. It means e-learning experience positively associated with technology proficiency. Technology proficiency (TP) has a positive correlation with EE and SES with the value of .767 and .800. The SP also has the highest correlation with EE and SES as its values are .917 and .915. All of these have a positive contribution toward student's employability skills. It also reinforces that student engagement and technology proficiency both of these have a significant impact on employability skills.

Multiple Linear Regression Analysis

It can be observed from the adjacent table that the standardized beta value acquired in the case of cognitive strategies (CS) is .273 which renders the construct as a significant predictor of students' employability skills (SES).

Table 4

Multiple Linear Regression Test

Coefficients ^a		Unstandardized Coefficients		Standardized Coefficients		95.0% Confidence Interval for B		
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	-.228	.048		-4.766	.000	-.321	-.134
	CS	.275	.027	.273	10.043	.000	.221	.329
	EE	.286	.044	.281	6.528	.000	.200	.372
	SP	.210	.041	.193	5.187	.000	.131	.290
	SE	.156	.035	.150	4.463	.000	.087	.224
	TP	.138	.021	.141	6.460	.000	.096	.180

a. Dependent Variable: SES

Likewise, in the case of e-learning experience (EE) the sig value achieved is .000 which demonstrates the presence of a strong and linear relationship. In addition to this, the outcomes of student perception (SP) highlights that the p-value is .000, which is well below the standard significance threshold of .05, thus illustrating that student perception is a statistically significant predictor of student employability skills (SES).

Furthermore, the outcomes regarding student engagement (SE) highlights that the construct is a statistically significant predictor of student employability skills (SES), which is further bolstered by the p-value of .000 derived in this regard, which is well within the required threshold of .05. The findings demonstrate that higher levels of engagement in academic and learning activities contribute positively to how students perceive their readiness for employment. In a similar vein, the outcomes for technology proficiency (TP) with a p-value of .000 and unstandardized coefficient beta value of .138 suggests the presence of a strong and statistically significant interrelationship.

Mediating Effects for Sobel Test

Input:		Test statistic:	p -value:	
t_a	25.900	Sobel test:	15.44634336	0
t_b	19.243	Aroian test:	15.43893045	0
		Goodman test:	15.45376697	0
		Reset all	Calculate	

Fig. 3 Sobel Test for Cognitive Strategies

The test statistics value for sobel is 15.44, for Goodman 15.45, and for Aroian 15.43. Based on these values, it has been clearly understood that p values for the Technology Proficiency (TP), Student's Employability Skills (SES), and Cognitive Strategies (CS) are corresponding with 0.001. It ensures the statistically significant and indirect effect of cognitive strategies on employability skills by technology proficiency.

Input:		Test statistic:	p -value:	
t_a	25.900	Sobel test:	17.28252349	0
t_b	23.204	Aroian test:	17.27538187	0
		Goodman test:	17.28967398	0
		Reset all	Calculate	

Fig. 4 Sobel Test for E-Learning Experience

The sobel, Aroian, and Goodman scores for this variable are 17.28, 17.27, and 17.29 respectively. All of these values are greater than 1.96 that refers to a significant mediating impact of technology proficiency in this study.

Input:		Test statistic:	p -value:	
t_a	25.900	Sobel test:	16.40090091	0
t_b	21.191	Aroian test:	16.39358312	0
		Goodman test:	16.40822851	0
		Reset all	Calculate	

Fig. 5 Sobel Test for Student Perception

Based on the result of the above figure, the sobel, Aroian, and Goodman values have been determined to be 16.40, 16.39, and 16.40. The magnitude of the test values also represent that student perception on employability not only has a direct effect, but also has an indirect influence through technology proficiency.

Input:		Test statistic:		p -value:
t_a	25.900	Sobel test:	16.10355465	0
t_b	20.561	Aroian test:	16.09619683	0
		Goodman test:	16.11092258	0
<input type="button" value="Reset all"/>		<input type="button" value="Calculate"/>		

Fig. 6 Sobel Test for Student Engagement

This relationship also has a strong test statistic score as the values for sobel, Aroian, and Goodman are 16.10, 16.09, and 16.11. It refers to a high significant mediating impact of technology proficiency.

Conclusion

The discussion of this study concludes that student's readiness toward the utilisation of AI have a significant impact on technological proficiency, which acts as a mediating variable in this research to impact on employability skills. The findings also explore that cognitive strategies, student perception, e-learning experience, and student engagement have a positive contribution on employability outcomes. On the other hand, technology proficiency also has a significant direct and indirect impact. It has been demonstrated that e-learning experiences have the strongest impact that underscore the significance of digital platforms in technology driven workplace preparation. The use of constructivist learning theory emphasises that learners develop actively through interaction and experience with their environment. When the students are ready to use artificial intelligence, they are not the passive recipients but referred to as active participants to develop meaning for learning experiences. Practically, the hypothesis indicates the significance of fostering AI readiness among university students in China to enhance their technological competence and employability. The Chinese universities can design workshops, training programs, and project-based learning activities. It integrates AI tools into the curriculum by enabling students to practice problem solving in real-world contexts.

The overall result indicates the needs for AI integration in universities for active learning engagement and digital literacy. The study on the relationship between student learning readiness to use AI, employability skills, and technological competencies in Chinese universities face certain limitations. Initially, the self-reported readiness of the students may not fully reflect their actual competence to create potential bias. The rapidly evolving nature of AI technologies highlights the findings that may become outdated quickly. The future research on student learning readiness to use AI for employability skills development in Chinese universities can expand in several directions. Comparative studies on different regions or international contexts can highlight institutional and cultural differences in AI adoption. The longitudinal study can also be used to track how competence and readiness evolve throughout the academic journey of the students and their transition into the workforce.

Ethical Statements

This study was conducted in line with institutional and international ethical research standards.

Statements and Declarations

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged.

Competing Interests

The authors disclose that they have no conflicting interests.

Ethical Statements

The people who conducted this study obtained consent from every participant before conducting the survey and informed them of keeping their confidentiality.

Informed Consent Statement

Informed consent was obtained from every individual participant involved in the study.

Author Contributions

All authors participated equally in the study's idea, design, data collection, analysis, and article writing.

Artificial Intelligence (AI) Usage

Artificial intelligence techniques were employed purely for language improvement and grammatical correction, and did not impact the study design, methodology, or conclusions.

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