

AI, Cognitive Expression and Language Proficiency as Drivers of Student Employability: An Empirical Investigation

Osheen Kaur¹, Shalini Sharma², Sukhmani Kaur³

¹Research Scholar, Rayat & Bahra University, Mohali, Punjab, India, osheenkaurpadam@gmail.com

²Department of English, UILAH, Chandigarh University, Mohali, Punjab, India, shalinisharma.cgc@gmail.com; shalini@cumail.in

³Department of Commerce, USB, Chandigarh University, Mohali, Punjab, India, sukhakal313@gmail.com

Abstract

Employability for graduates relies on an increasing level of technological, cognitive and communication skills. The study aims to test the stated hypothesis as laid for the study which is whether the Employability Skills (ES) of students can be significantly predicted by the variables of Artificial Intelligence (AI), Cognitive Expression (CE) and Language Proficiency (LP). Descriptive and quantitative analysis with cross sectional design was used for data collected from 202 students at the university by using a structured questionnaire. The Cronbach's alpha, descriptive statistics, Kolmogorov-Smirnov and Shapiro-Wilk tests were utilized to analyze scale reliability and distributional properties. To look at the association between constructs, Spearman rank correlation was used and multiple linear regression and collinearity diagnostics used to determine the predictive contribution of AI, CE and LP for employability skills. Scale reliability was found to be satisfactory to good as per (Cronbach's alpha between 0.719 and 0.830). The three predictors have a positive effect and are significantly associated with employability skills. Cognitive Expression had the largest standardized effect ($\beta = 0.413$, $p < 0.001$), followed by Language Proficiency ($\beta = 0.305$, $p < 0.001$) and Artificial Intelligence ($\beta = 0.160$, $p = 0.004$). The regression model shows a significant status, $F(3, 198) = 80.876$, $p < 0.001$, and accounted for 55.1% of the variance in employability skills ($R^2 = 0.551$; adjusted $R^2 = 0.544$). According to the results, a balanced approach to graduate employability that focuses on developing a mixture of technological competences, cognitive skills and communication skills. Universities and colleges thus integrate AI literacy into the activities that foster reasoning, cognitive expression, and language skills. Three capability areas were explored in one predictive model, providing empirical evidence to complement the employability research literature and implications for integrated curriculum and employability interventions. The results also assist towards the basis for future

multi-institutional and longitudinal research into the evolution and impact of these competencies on graduate employment.

Keywords: Artificial intelligence; cognitive expression; language proficiency; employability skills; higher education; graduate employability; AI literacy; communication skills

1. Introduction

The issue of employability has been emerging as an important concern in higher education, as transition from University to employment is determined by more than academic knowledge. Graduates are expected to communicate effectively, think critically, work with digital technologies effectively and respond to the changing demands of the workplace. Signalling theory, human capital theory, social resources, and the ability to translate one's human capital into value in the workplace are all dimensions of employability that have been highlighted by recent research (Suleman, 2021). The focus is important in consideration to the reference to the evolving nature of work with the skill sets as required for graduates because of the impact of artificial intelligence.

Artificial Intelligence is no longer a niche technological area but is increasingly becoming part of teaching, learning, and the professional world. AI-powered educational resources can provide personalised feedback, adaptive learning experiences, and ease support and practice. To date, a considerable amount of systematic research has linked AI literacy to digital competence, motivation, positive attitudes, and AI self-efficacy, and has identified measurement and self-assessment concerns (Biagini, 2025; Lintner, 2024). However, based on the evidence found in higher education, generative AI could positively impact cognitive, technical, and interpersonal skills, but this is highly contingent on how it is used pedagogically (Daniel, 2025).

AI cannot, however, replace human skills with regard to employability. The skills of critical thinking, communication, judgement and explaining ideas remain vital to effective participation in organisations. Recent critiques of AI in higher education highlight the need for the integration of AI use alongside the cultivation of critical thinking and problem-solving skills (Liang, Stephens and Brown, 2025). Likewise, contemporary work on AI literacy defines it more broadly to include critical, ethical, and socially responsible engagement with AI systems (Biagini, 2025; Zhang, Prasad and Schroeder, 2025).

Another basic component of employability is language proficiency. Graduates must be able to share ideas, interpret information, interact in negotiating meaning, work cooperatively and adapt messages for different audiences in order to communicate in the workplace. Thus, language ability not only ensures a person's ability to communicate in the language, but it also enables the expression of other competencies. While a graduate may possess very high technical and cognitive skills, these skills may not be well expressed and valuable in the workplace.

Technological competence and cognitive ability and communication ability are increasingly coming together in the transition from higher education to employment. Being disciplinarily trained is no longer enough to demonstrate 'sustained' employability in today's labour market. Employers are placing greater emphasis on digital and artificial intelligence (AI) skills in combination with excellent cognitive skills, communication, adaptability and problem-solving in real-life workplace settings in today's world. The widespread adoption of generative AI (GenAI), automation, and decision-making which is derived from data has also reshaped the skills set required of university graduates. Employment readiness can therefore be defined as a multi-dimensional capacity and is beyond the acquisition of technical skills. Thus it comprises the capacity to use knowledge, communicate effectively, reason using critical thinking, solve problems and adjust to technologically changing work environments.

In this transformation, artificial intelligence (AI) plays major role, as it is also reshaping the nature of work and how students master their professional skills. Personalised learning, automated feedback, information processing, content generation, language development and problem solving can be facilitated with the help of AI applications. New studies suggest that the use of AI with deep learning is becoming linked to students' views on employability. Wut et al. (2025) found a correlation between perceived AI literacy and employability in a partial least squares structural equation modelling study with university students. The results imply that the knowledge students perceive they have about AI can be a valuable asset to their job opportunities, further evidence that AI proficiency is part of the new graduate skill set. Research on university graduates also has found that an increase in knowledge with the application of AI tools, such as generative tools, is linked to working in occupations related to graduates' academic specialisation and to self-reported increases in productivity of the individuals in terms of professional alignment (Portocarrero Ramos et al., 2025).

But the role of AI in employability goes beyond how well it can be used to leverage specific technological tools. 21st-century skills in AI competence now include problem-solving, assessing AI-produced content, critical interpretation of content with AI. This is relevant because over-reliance on AI might not necessarily lead to transferable skills in the workplace. Incorporating AI with higher order cognitive capacities is important, not replacing them; an analysis of 640 papers from the Scopus database via a 2025 bibliometric and systematic review of the literature on generative AI and topics related with critical thinking in higher education. The review highlights areas of interest from the emerging literature, namely critical thinking, AI literacy, personalised learning and adaptive instructional approaches (Wana et al., 2025). Therefore, cognitive skills that help learners to question, analyse, evaluate and creatively apply information are most relevant to employability in the context of AI proficiency.

In higher education, the connection between AI and cognitive development is especially important as employability demands that students be able to apply what they have learned to unfamiliar and complex scenarios in the workplace. Cognitive skills that involve critical thinking, analytical reasoning, problem-solving, creativity, decision making and metacognition helps learners from knowledge acquisition to knowledge application. The evidence for the educational value of GenAI is mixed, but there is some recent meta-analytic evidence. The systematic review and meta-analysis of the study (Chen and Cheung, 2025) examined the impact of GenAI on the overall learning outcomes of university students across 57 studies and 97 effect estimates. They discovered a positive effect of GenAI on language skills, academic achievement and higher-order thinking, though the effect on metacognition was not significant. This is especially significant for employability because it suggests that reflection and self-monitoring and independent judgement, skills that are deliberately taught, may be supported through AI-based learning and yet be a key cognitive outcome to strengthen.

AI must then be seen as a catalyst in a larger employability system, not as a deciding factor in employment. This is borne out by evidence from employability interventions using AI. To explore an AI-based teacher in a nine-lesson course on employability skills and on transferable skills, (Aditya et al., 2024) the study conducted a multi-national study with 207 students in higher education from three countries. The study showed that the AI-supported learning intervention was very engaging and satisfying, highlighting the core potential of conversational AI in supporting education in various institutional contexts. Further evidence from “Computers and Education: Artificial Intelligence” indicates that a well-designed 12-week AI unit increases

students' AI knowledge, help upgrade their skills and capabilities, and that greater AI capital is linked to better employment outcomes upon graduation. The study posited a progression from AI assisted learning to AI capital and then to AI jobs, implying that structured education exposure could have a more significant impact than just using AI tools (Drydakakis, 2025). However, in increasingly internationalised labour markets, language competence, especially in English, is also a key factor in graduate employability, in addition to AI and cognition. English is not only an academic subject, but a means of professional communication, professional collaboration, professional documentation, professional presentations, professional interviewing, professional negotiation and professional interaction in the workplace. Graduates can have the appropriate technical knowledge but have problems in job situations if they are unable to clearly and appropriately communicate their knowledge. A large number of studies of graduates' transitions to work have revealed problems with workplace genres, workplace discourse and communication, some of which stem from insufficient English language proficiency and insufficient knowledge of the field (2021).

Empirical evidence from India recently gathered from experiments supports the link between English proficiency and employability. A large-scale randomized field experiment among 1260 low-income workers in Delhi found that the intervention to increase English proficiency among the participants led to an overall improvement in English proficiency, employability and estimated wages (Loyalka et al., 2025). This is important because the study measured employability using the self-perceptions of the students, as well as the evaluations by hiring managers. This is significant evidence in the context of Indian higher education where English remains an important language of professional and organisational communication.

There are multiple dimensions to language competency and employment, as it takes more than linguistic accuracy to be effective at work. Language competence helps graduates to build grammatically correct messages as well as express their cognitive, technical and professional skills in meaningful contexts. A graduate might have analytical reasoning, problem solving and decision making skills, but these skills must be expressed in effective ways via interviews, reports, presentations, emails, meetings, discussions and collaborative interactions. According to the study by (Wahab et al., 2024) on graduate employability also found that communication, interpersonal and problem-solving skills are crucial aspects of the 'employability' construct. Therefore, good language skills may serve as a communicative tool to bring graduate academic knowledge and cognitive abilities to the fore of the employers. Professional English proficiency

in this context can help to transfer academic knowledge and skills into workplace performance, especially in workplace settings that involve international communication and digitally mediated workplace interaction.

The potential benefits of AI, alongside cognitive skills and language proficiency, then make a compelling case for revisiting employability development in higher education. These three dimensions are not mutually exclusive skills but may be integrated into the modern graduate skill set. AI proficiency includes the capacity to comprehend, assess, and utilize AI tools, whereas cognitive skills involve thinking, reasoning, problem-solving, inventiveness and judgment. Knowing a language, in turn, helps people to share knowledge and ideas in an effective way in academic and professional settings. Recent studies show that AI literacy, these days is becoming more associated and connected with how students see themselves being prepared for the emerging forms of work, with knowledge of AI and its productive use being relevant aspects of graduates' training (Wut et al., 2025). In current technological landscape where AI systems are generating substantial information and content, information literacy also entails the ability to locate, assess and use information responsibly in the right manner. (Miller et al., 2024).

These competencies will interact in a crucial way, as AI as a tool supports and extends human cognitive abilities. AI aid language learning by giving immediate individualized feedback, assists conversational practice, writing support, translation, and content creation, as well as adaptive learning. Cognitive skills allow students to ask questions of AI-generated information, identify its strengths and weaknesses, assess its credibility and make their own judgements. The critical thinking research in professional education shows the continuing importance of higher order thinking in order to prepare professionals to transfer knowledge to the industry's context, especially for the use of knowledge in complex and critical situations (Wynekoop & Nakatani, 2024). This communicative power is then realized in the ability to express, negotiate, and apply AI-assisted knowledge and cognitive judgments in professional contexts via language skills. Thus, the three competencies can be regarded as reinforcing resources to support graduates' abilities to engage successfully in increasingly technology-mediated workplaces.

Nevertheless, the association must not be taken as being necessarily causal. Like being proficient in English or cognitive capacity, the use of or acquisition of AI is not a sufficient qualification for securing employment. These competencies are shaped by contextual factors,

such as students' disciplines, quality of education, opportunities for experiential learning, access to different digital technologies, adds more to institutional support and expectations and opportunities to apply competencies in real work settings. The relevance of generic skills, workplace exposure, employer engagement and curriculum design, instead of a single competency to explain employability has been emphasized in recent research on graduate employability (Wahab et al., 2024). Thus, competence in AI must be placed in a wider competency-development context, involving technological skills, cognitive, communicative and experiential aspects.

AI competence represents technological and AI-related capability; cognitive skills represent higher-order thinking and information-evaluation capability; and language proficiency represents the ability to communicate knowledge and professional competencies effectively. Together, these competencies constitute complementary dimensions of graduate human capital that may contribute to employability skills.

AI competence is the knowledge, understanding and skills students have in using AI enabled technologies effectively and responsibly. Increasingly, contemporary understandings of competence in the world of AI include cognitive, ethical and affective aspects of interaction with an AI system (Ahmad et al., 2025). Cognitive skills include critical thinking along with creativity, analytical reasoning, problem-solving skills and decision-making, allowing students to analyze, evaluate, and apply knowledge to novel situations. Language proficiency is the capacity to communicate effectively and appropriately in academic and professional environments, orally, in writing and in interpersonal and workplace settings. Employability skills include communicating, working in a team, being adaptable, competent at work, problem-solving, using digital tools and being ready for the workplace. This multi-dimensional view of employability is in line with the modern employability research which views employability of graduates as a combination of cognitive, communication, technological, interpersonal and adaptive skills, as opposed to subject-matter knowledge (Adam et al., 2025).

This holistic model addresses the evolving needs of an AI-driven workforce and the necessity of higher education to transcend its fragmented skill-building strategy. The proposed framework is not a separate domain for linguistic, cognitive and technological skills, but is a complementary set of human capital which can be combined to enhance the capability of students to enter, work and get adapted to modern workplaces. The argument is thus not that

being competent in AI, in cognitive skills or in languages on their own guarantees employment, but that a combination of these skills may give the graduates a more complex ability set to deal with employment environments that rely heavily on technology, knowledge, and communication. This is especially important because a major concern of employers is that graduates combine a knowledge and skill in technology with analytical thinking, communication, and transferable skills. Newly emerging lines of evidence on AI and graduate employability also indicate that higher education institutions must review curricula to ensure graduates acquire the skills needed in the rapidly evolving landscape of AI-driven working (Wut et al., 2025). The study's emphasis on Cognitive Expression which means to think, plan, and express reasoning clearly and critically. The idea is related to the value of thinking at higher levels and effective expression of ideas. The importance of employability is also evident when it comes to understanding problems, making judgements and explaining decisions in the recruitment process, and whilst working in the workplace. In the present research, however, the influences of AI, Cognitive Expression and Language Proficiency are not examined separately, but rather treated as a combination of these influences.

2. Literature Review and Theoretical Foundations

2.1 Employability as a multidimensional construct

One qualification or skill is not enough to measure graduate employability. As well as human capital (defined as core knowledge and different abilities acquired through academics and training), other factors of employability have been identified by traditional economic thinking, such as signalling, matching, social resources and personal circumstances (Suleman, 2021). This perspective on employability skills is demarcated as the capacity to get hold and advance in a job through the activation and expression of relevant capacities. (Byrne, 2022)

The reason for the importance of signaling is that the employer cannot observe all the attributes of a graduate during the recruitment process. Qualifications, communication performance, portfolios, demonstrations and observable behaviours can thus be used to give the indication of underlying competence. Research by employers suggests that graduates should have access to employability resources and demonstrate and communicate them effectively in recruitment and at work (Anderson and Tomlinson, 2021). Healy, Hammer and McIlveen, 2022)

2.2 Human Capital Theory

The first theoretical basis of the study is in terms of Human Capital Theory. Human Capital Theory is the first theoretical basis that will be used in the study. Becker (1964) saw education and training as investments to augment productive capacities. In the higher-education sector, this means that students develop knowledge and skills that may contribute to increased productivity and job prospects. AI literacy is considered as a new form of human capital where, students use, evaluate and interact with AI can be more prepared for digitally mediated tasks. Likewise, the capability to acquire the language and express one's thoughts is a transferrable skill that could enhance the productive aspect of education. (Kim, Kim and Tzokas, 2022)

Thus, the Human Capital Theory is used to anticipate positive connections among the variables of Artificial Intelligence, Cognitive Expression, Language Proficiency, and Employability Skills. (Bradley, Priego-Hernández and Quigley, 2022).

2.3 Signalling Theory

In a complementary way, Signalling Theory fills in the human-capital picture on how capabilities are made known to the employers. When decisions are made in an environment of information asymmetry, labour-market participants use observable signals to make those decisions, according to Spence (1973). For graduates, language competence and cognitive expression is easily demonstrated during interviews, presentations, written application, and group activities. Responsible and effective use of AI could also be assessed as a signal of AI literacy where it is presented in students' portfolios, projects or assessment contexts. The theory is thus that employability depends on the ability as well as capabilities which could be easily recognised by employers. (Perez-Encinas and Berbegal-Mirabent, 2023)

2.4 Social Cognitive Theory

The Social Cognitive theory is a behavioural model of employability capability development and application that is proposed by Bandura (1986). It highlights the mutual relationships between people, behaviour and environment. Students can build confidence and competence through observing, practicing, feedback and successful performance. Learning environments enabled by AI might afford opportunities for repetition and feedback, and cognitive expression and language skills could be enhanced by participation and communication. (Crompton and Burke, 2023)

This perspective is pertinent because the relationship as inbetween the use of AI and employability is unlikely to be captured by the technology. What AI can be helpful as a

development tool or not might depend on the learning environment, student engagement, and opportunity for practising and reflecting on skills. (Chan and Hu, 2023)

2.5 Technology Acceptance Model

The key and primary factors that account for the explanation of technology adoption according to the Technology Acceptance Model (TAM) are the perceived usefulness of the technology and perceived ease of use of the technology (Davis, 1989). Students who think that AI tools are helpful and manageable are more likely to use them in learning activities in this study. However, capability to take up a technology is not the same as employment. In this context, AI is therefore seen as a tool to predict employability based on capabilities and is not seen as an automatic benefit of being exposed to technology.

2.6 Communicative competence and cognitive expression

The communicative competence theory is relevant to explaining the contribution of language to employability. (Hymes, 1972) extended the concept of language competence by emphasizing appropriate language use in regular social situations, and (Canale and Swain, 1980) highlighted four additional dimensions like grammar, sociolinguistic concerns, discourse and strategic usage of language. These dimensions are very similar to the demands of the workplace such as adapting communication to audiences, forming coherent explanations, and coping with communication problems.

At this point, Cognitive Expression comes in to the picture, emphasizing the organization and communication of thoughts. In higher education, there is growing overlap between critical thinking and the use of AI. Students must challenge, assess, and independently evaluate information and arguments produced by AI, and articulate their rationale for any conclusions. Systematic evidence for the past decade shows that AI and critical thinking are emerging as a topic of critical research in higher education. (Salido et al., 2025). (Barta et al., 2022)

2.7 AI literacy and employability

AI literacy is no longer just about being familiar with AI applications but rather a comprehensive capability. In recent years, the reviews that have been published with the focus on functional, critical, ethical, and sociocultural aspects of AI education and training, highlighting the need for education to involve the students with the ability to use AI tools effectively and critically (Biagini, 2025); (Zhang, Prasad and Schroeder, 2025). Strong correlations are also reported in a systematic review between AI self-efficacy with literacy,

promoting favourable attitudes, motivation, and digital competence, and there is also a link between the two measures of self-efficacy. However, there are also cases in which self-efficacy does not match other measures of competence. (Bond et al., 2024); (Delcker et al., 2024)

This is significant from the study where it marks on the fact that students might feel confident in using AI, but this is not enough to add value to employability; their judgement, capability to communicate mark that impression. To this end, AI is considered in the context of Cognitive Expression and Language Proficiency rather than as a standalone answer to employability. (Chiu et al., 2024)

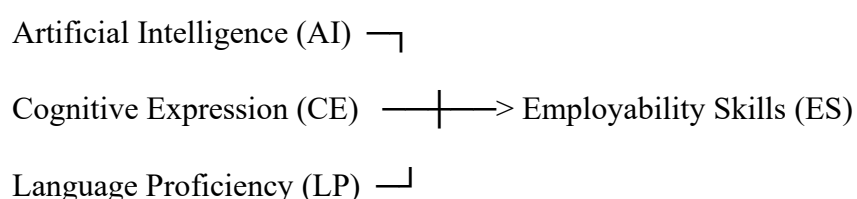
2.8 Research gap

There is ample existing literature that reflects the separate significance of the three themes of digital capability, cognitive skills, and communication competence, but they are examined separately. AI research in higher education tends to focus on learning outcomes or on technology use, while employability research tends to focus on broader human-capital and career resources. To address this, this study tests a focused empirical model that includes the three variables: AI, Cognitive Expression, and Language Proficiency, all of which predict Employability Skills (Karaca-Atik et al., 2023); (Scandurra et al., 2024).

3. Conceptual Framework and Hypotheses

The conceptual framework is based on the assumption that Employability Skills are linked to three complementary capability areas: Artificial Intelligence, Cognitive Expression and Language Proficiency. AI refers to the technical skill required to operate within an environment that supports AI (artificial intelligence); Cognitive Expression is the ability to think and express ideas clearly; Language Proficiency is the skill to use language effectively in academic and work settings.

From a conceptual point of view, the model can be expressed as follows:



3.1 Hypothesis development

H1: Artificial Intelligence is significantly associated with students' Employability Skills.

H2: Cognitive Expression is significantly associated with students' Employability Skills.

H3: Language Proficiency is significantly associated with students' Employability Skills.

H4: Artificial Intelligence, Cognitive Expression and Language Proficiency jointly explain a significant proportion of variance in students' Employability Skills.

4. Research Methodology

4.1 Research Design

A descriptive, quantitative, cross-sectional survey design was used to investigate the relationship of Artificial Intelligence, Cognitive Expression, and Language Proficiency with students' Employability Skills.

4.2 Sample Size and applied Sampling Technique

Primary data has been collected from 202 students ($N = 202$) using a structured, self-administered questionnaire.

- Report the sampling frame, sampling technique, institution/city/country, demographic profile and response rate.

4.3 Variables of the Study

Table 1: Variables construct

Variable	Type	Description
Artificial Intelligence (AI)	Independent	Students' perception of AI tools/technologies aiding learning and skill-building
Cognitive Expression (CE)	Independent	Students' ability to think critically and express ideas clearly
Language Proficiency (LP)	Independent	Students' command over language for effective communication
Employability Skills (ES)	Dependent	Students' overall readiness and skill set for employment

Source: Author compilations

Table 1, specifies the variables considered for the study with the clear mention of the Independent & Independent variable for the study targeting the objectives.

4.4 Statistical Tools Used

Data were analyzed using various statistical techniques that examine reliability, distributional properties, associations and predictive relationships among constructs. The internal consistency has been accessed through Cronbach's alpha and response patterns were summarised using mean (M), standard deviation (SD), skewness and kurtosis. The Kolmogorov–Smirnov and Shapiro–Wilk procedures were used to examine distributional normality. AI, CE, LP and ES were compared using Spearman's rank-order correlation with the purpose of determining and knowing the direction and strength of the relationships between these variables. Multiple linear regression was applied to assess the contribution of AI, CE and LP to ES, including a Model Summary, ANOVA and Coefficients output. Tolerance and Variance Inflation Factor (VIF) statistics were used to check for possible multicollinearity among the independent variables. Data exported from SPSS were used for conducting all analyses at a 95% level of confidence ($\alpha = 0.05$).

5. Data Analysis and Interpretation

5.1 Reliability Analysis (Cronbach's Alpha)

Table 2: Reliability of Study Constructs (Cronbach's Alpha)

Variable	Cronbach's Alpha	N of Items	Reliability Level
Employability Skills (ES)	0.830	5	Good reliability
Artificial Intelligence (AI)	0.819	4	Good reliability
Cognitive Expression (CE)	0.734	5	Acceptable reliability
Language Proficiency (LP)	0.719	5	Acceptable reliability

Source: Authors Calculations

Table 2, shows the reliability analysis which reveal that Cronbach's Alpha coefficient for each of the four constructs ranges from above 0.70, which is the generally accepted level for the test, thus demonstrating satisfactory internal consistency. Employability Skills ($\alpha = 0.830$), Artificial Intelligence ($\alpha = 0.819$), Cognitive Expression ($\alpha = 0.734$) and Language Proficiency

($\alpha = 0.719$) have acceptable reliabilities. The scales can then be said to be appropriately valid for further statistical analysis.

5.2 Descriptive Statistics

Table 3: Descriptive Analysis (N = 202)

Variable	N	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis
ES	202	1	4.40	2.387	0.772	0.596	-0.535
AI	202	1	5.00	2.578	0.835	0.697	-0.397
CE	202	1	4.60	2.714	0.685	0.469	-0.020
LP	202	1	4.60	2.779	0.685	0.469	0.414

Source: Author Calculations

In table 3, the response scale is "reverse coded" (1 = Strongly Agree), so that the mean scores for all four constructs are less than the neutral point of 3.0. This means an overall pattern of consensus. The mean for Employability Skills is 2.387, indicating the highest level of agreement overall that the respondents have good employability skills.

The median scores for the three types of AI are: Artificial Intelligence: 2.578; Cognitive Expression: 2.714; Language Proficiency: 2.779. The latter two show somewhat more moderate agreement, and are closer to the neutral point. Skewness ranges from -0.02 to 0.70 and kurtosis from -0.54 to 0.41. The values are still within ± 1 , and the distributions are considered to be reasonably symmetric and close enough to normal for analytical purposes.

5.3 Test of Normality

Table 4: Normality Analysis

Variable	K-S Statistic	df	K-S Sig.	Shapiro-Wilk Stat.	df	S-W Sig.
----------	---------------	----	----------	--------------------	----	----------

ES	0.081	202	0.003	0.980	202	0.006
AI	0.082	202	0.002	0.979	202	0.005
CE	0.088	202	0.001	0.987	202	0.069
LP	0.105	202	0.000	0.975	202	0.001

Source: Author Calculations

In table 4, the most constructs in the Kolmogorov–Smirnov and Shapiro–Wilk fall out with the results that have values less than 0.05. As such, this suggests that the observed distributions are distinct from a normal distribution, in a strict sense.

With a moderately large sample of 202, it is not unusual to find such a result for ordinal Likert-scale responses as normality tests can detect very small departures from normality as sample sizes increase.

However, skewness and kurtosis statistics do not differ significantly from the acceptable range of ± 1 and the sample size is greater than 30, thus supporting the use of parametric procedures like multiple regression. As a non-parametric robustness check, Spearman's rank correlation was also used.

5.4 Correlation Analysis (Spearman's Rho)

Table 5: Correlation Analysis

Variable	ES	AI	CE	LP
ES	1.000	0.477**	0.687**	0.631**
AI	0.477**	1.000	0.510**	0.326**
CE	0.687**	0.510**	1.000	0.612**
LP	0.631**	0.326**	0.612**	1.000

**** Correlation is significant at the 0.01 level and is observed 2-tailed**

Source: Author Calculations

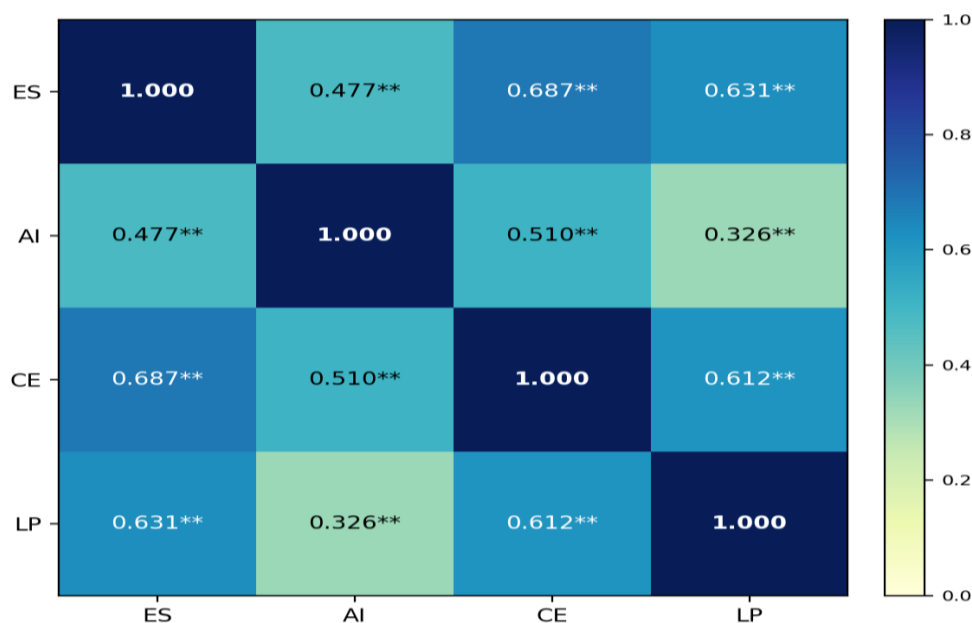
Table 5, shows the Pearson correlation values of Experiential Skills (ES), Artificial Intelligence (AI), Cognitive Engagement (CE) and Learning Performance (LP). The results show that all variables are significantly as well as positively correlated at the 0.01 level which is 2 tailed, which means that there is the meaningful association among the constructs.

The positive association between experiential skills and cognitive engagement is relatively high ($r = 0.687$) for the strongest correlation. There is also a significant and (+ve) positive correlation

between ES and LP ($r = 0.631$), which indicates that if students are more skilled in their experiences then they are more likely to perform well in their learning. The same relationship can be observed between CE and LP ($r = 0.612$), which shows that there is a positive correlation between the cognitive engagement and the learning outcomes of the students.

There is a moderate and positive (+ve) correlation between AI and CE ($r = 0.510$), and a moderate (+ve) positive correlation between AI and ES where, ($r = 0.477$). The less significant correlation is between AI and LP ($r = 0.326$) but still significant. In general, the results indicate that ES and CE are more strongly correlated with LP than AI, and that the positive relationships between all variables are significant, suggesting preliminary evidence of the interconnectedness of these variables. But correlation does not prove causation.

Fig 1: Spearman's Correlation Matrix among Study Variables



Source: Author calculations

Interpretation

Figure 1, shows the correlation values of all study variables are found to be positive and significant at 1% level ($p < 0.01$). Cognitive Expression has the highest bivariate correlation with Employability Skills ($r = 0.687$) while Artificial Intelligence has the lowest bivariate correlation with CE, $r = 0.477$. As the scale is reverse coded, a positive correlation would suggest that higher scores as reflected on one scale correspond to higher scores as available on the other, such that students who score higher on AI, CE, and LP also score higher on

employability skills. The inter-correlations of the predictors ($AI = 0.510$, $CE = 0.326$, and $LP = 0.612$) indicate that these are related, but not overlapping constructs, and further investigated with collinearity diagnostics.

5.5 Multiple Regression Analysis

To evaluate the combined effect and each individual effect of (AI), (CE) and (LP) on (ES) multiple linear regression was performed.

5.5.1 Model Summary

Table 6: Proportion of Variance in Employability Skills (ES) as mentioned with AI, CE and LP

R	R Square	Adjusted R Square	Std. Error of Estimate	Durbin-Watson
0.742	0.551	0.544	0.521	1.978

Source: Author calculation

Multiple correlation coefficient (R is 0.742), which shows a very high (+ve) positive correlation between the set of predictors and Employability Skills. Table 6, The R Square value of 0.551 indicates that 55.1% of the variance in ES is explained by the combination of AI, CE and LP, suggesting a significant explanatory power for a behavioural and social-science model. Adjusted R Square value is 0.544 which is close to R Square and implies that the model is not materially being inflated by the additional predictors. The Durbin–Watson statistic 1.978 is near to 2, and there is no evidence of useful residual autocorrelation and the independence-of-errors assumption.

5.5.2 ANOVA

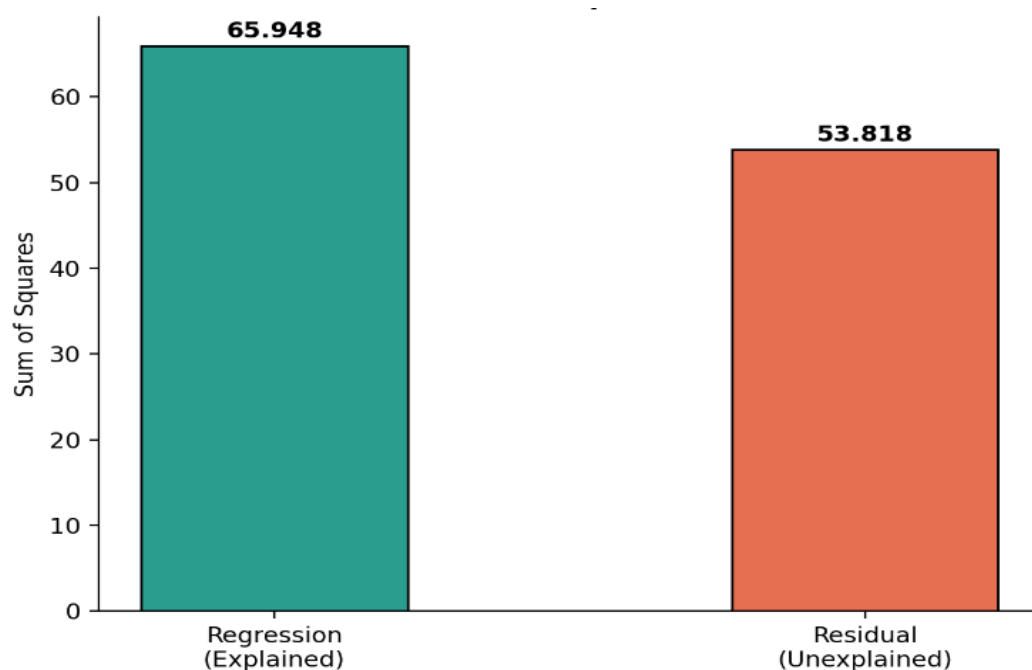
Table 7: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	65.948	3	21.983	80.876	0.000
Residual	53.818	198	0.272		
Total	119.767	201			

Source: Author calculation

The ANOVA output in table 7, is statistically significant, $F(3,198) = 80.876$, $p = 0.000$, at the 1% level. This means to certify that all of the regression model is a good fit, and that the three variables together (AI, CE, and LP) contribute significantly to the Employability Skills. Because $p < 0.05$ as the Null Hypothesis, which ultimately states that the three predictors do not have a combined effect on ES, is rejected.

Fig 2: ANOVA — Explained vs Residual Variance ($F=80.876$, $P<0.001$)



Source: Author calculations

Figure 2, illustrates the ANOVA results, showing that the regression model explains **65.948** units of variance compared with **53.818** unexplained variance. The significant F-value ($F = 80.876$, $p < 0.001$) indicates that the model provides statistically significant explanatory power.

5.5.3 Regression Coefficient

Table 8: Standardized Regression Coefficients (Beta) of AI, CE and LP on ES

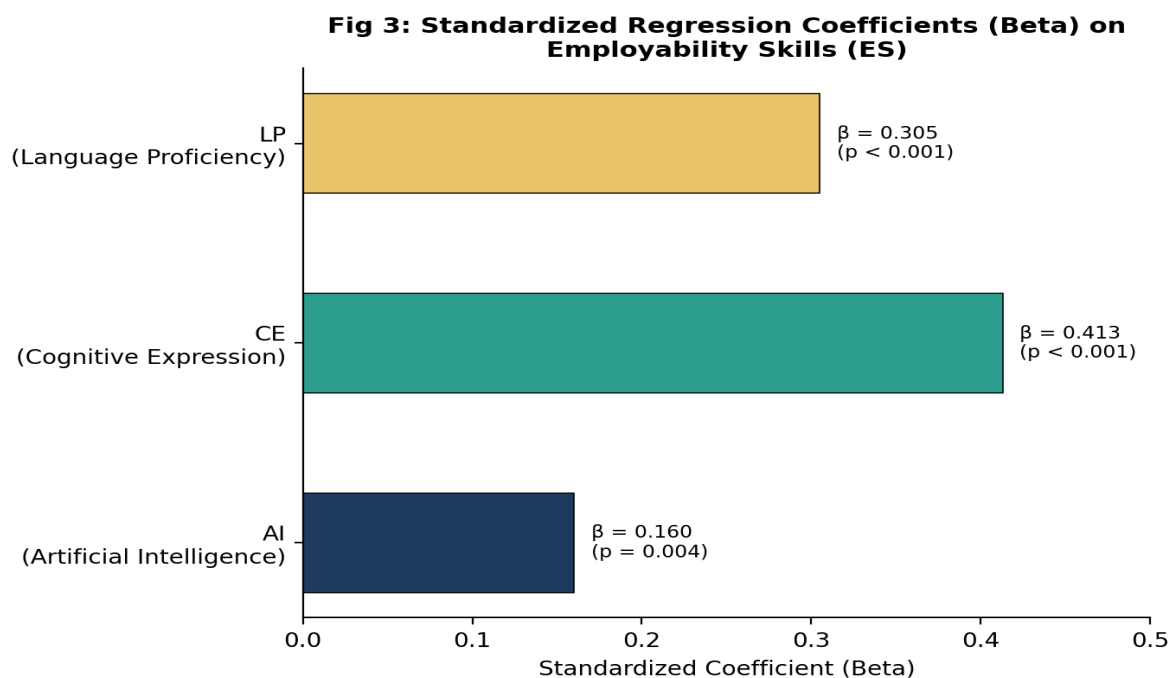
Model	B	Std. Error	Beta	t	Sig.	VIF
(Constant)	-0.216	0.173	—	-1.248	0.214	—

AI	0.148	0.051	0.160	2.912	0.004	1.331
CE	0.466	0.075	0.413	6.193	0.000	1.964
LP	0.344	0.070	0.305	4.937	0.000	1.686

Dependent Variable: Employability Skills (ES)

Source: Author Calculations

Fig 3: Standardized Regression Coefficients (Beta) on Employability Skills (ES)



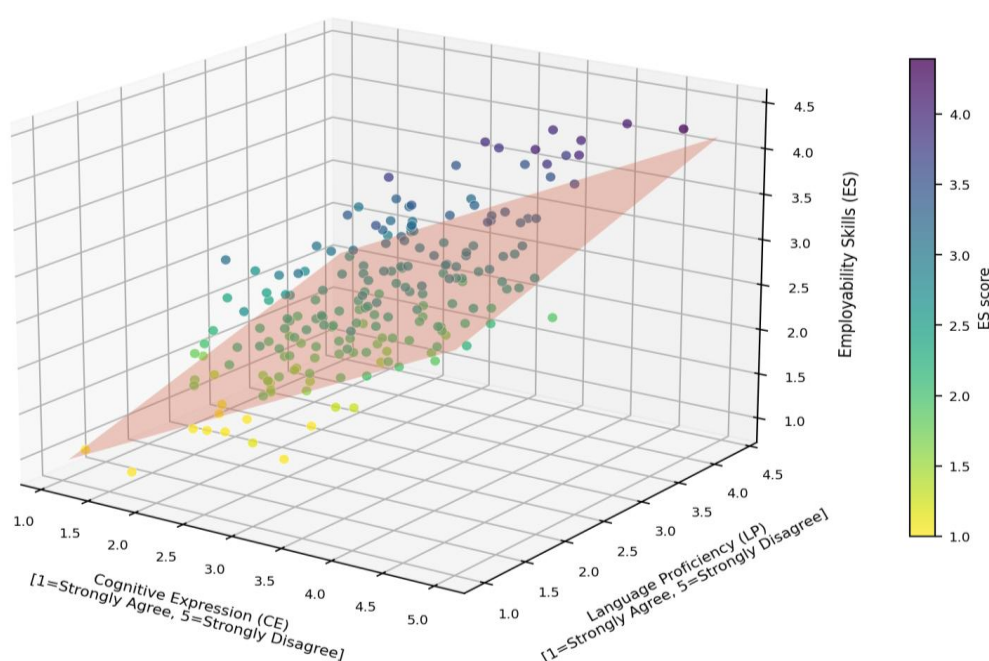
Source: Author calculations

The results as per Table 8, indicate that all of the independent variables are significant predictors of Employability Skills ($p < 0.05$). Cognitive Expression has the largest standardized coefficient (Beta = 0.413, $t = 6.193$, $p = 0.000$), followed by Language Proficiency (Beta = 0.305, $t = 4.937$, $p = 0.000$) and Artificial Intelligence (Beta = 0.160, $t = 2.912$, $p = 0.004$). The estimated regression equation as per the calculation is $ES = -0.216 + 0.148(AI) + 0.466(CE) + 0.344(LP)$. The positive B/Beta coefficients (Figure 3) suggest that as the predictor (ES, cognitive expression, language proficiency) increases, so does the agreement that the predictor supports the process of development, which is the same direction as the agreement that the employability skills are well developed. The problematic multicollinearity issue does not seem to exist between AI, CE and LP because VIF values are less than 5 and even less than a more conservative value of 3, and tolerance values are greater than 0.5.

5.5.4 3D Regression Plot

To view the combined regression relationship in three dimensions, the regression relationship is graphed along with the two strongest predictors, namely Cognitive Expression (CE) and Language Proficiency (LP). This figure represents a simulated sample designed to match reported means, standard deviations, and Spearman correlation values of ES, CE, and LP that are representative of the actual observations on the response level, which were not available in the source file. The number shown, then, is representative of the relationship that has been fit, not of the 202 original observations.

Fig. 4: 3D Regression Plot- Employability skills as a function of Cognitive Expression and Language Learning with Fitted Regression Plane



Source: Author calculations

The general trend is upward from the lower CE/LP region to the upper CE/LP region, giving a visual aid for the positive relationships found in the regression results (figure 4). The fitted plane corresponds to the estimated regression surface of ES with respect to CE and LP, and the dispersion of the points around the plane is due to the relatively high proportion of the variance explained by these variables.

The low value corner of the CE-LP surface (near 1), indicates the highest degree of agreement as the Likert responses are reverse coded. The figure shows that those who agree more with

the CE statement report lower, more agreeable ES scores, following the interpretation of the positive associations reported above, for those who agree more with the LP statement.

5.5.5 Collinearity Diagnostics

Table 9: Collinearity Analysis

Dimension	Eigenvalue	Condition Index	(Constant)	Variance Prop. — AI/CE/LP	Comment
1	3.891	1.000	0.00	Low	Baseline dimension
2	0.057	8.260	0.07	Low-Moderate	No concern
3	0.032	10.957	0.91	Moderate	No concern
4	0.020	13.971	0.02	Moderate-High	Within acceptable limit (<30)

Source: Author Calculations

The condition indices are all substantially below the critical value of 30 (Table 9). This indicates that multicollinearity does not present a serious problem in the regression model and that the estimated coefficients are reasonably stable.

5.5.6 Residuals Statistics

Table 10: Residual statistics

	Minimum	Maximum	Mean	Std. Deviation
Predicted Value	0.743	4.065	2.387	0.573
Residual	-1.665	1.326	0.000	0.517
Std. Predicted Value	-2.871	2.929	0.000	1.000
Std. Residual	-3.193	2.542	0.000	0.993

Source: Author calculations

Table 10, shows the residual mean is 0.000, which agrees with one of the assumptions of linear regression. Furthermore, the standardized residuals are mostly in the range of ± 3 , indicating that no extreme observations are likely to have influenced the results of the model.

6. Hypothesis Testing

Table 11: Summary declaring the results

H No.	Hypothesis Statement	Beta	Sig. (p)	Result
H1	Artificial Intelligence (AI) has a significant impact on Employability Skills (ES)	0.160	0.004	Supported
H2	Cognitive Expression (CE) has a significant impact on Employability Skills (ES)	0.413	0.000	Supported
H3	Language Proficiency (LP) has a significant impact on Employability Skills (ES)	0.305	0.000	Supported
H4	AI, CE and LP jointly have a significant combined impact on Employability Skills (ES)	R ² =0.551	0.000	Supported

Source: Author compilations

Table 11, declares the hypothesis testing with the supportive results.

7. Results and Discussion

All four of the hypotheses are accepted at the 5% significance level. Individual contributions of students' Employability Skills from Artificial Intelligence, Cognitive Expression and Language Proficiency are all statistically significant and the three predictors are also significant together.

Results indicate that Employability Skills is statistically related to a set of technological, cognitive and language-related skills. The most salient result is that of the relative contribution of Cognitive Expression. The standardized coefficient ($\beta = 0.413$) is much higher than the AI coefficient ($\beta = 0.160$), suggesting that the capacity to formulate, structure and communicate ideas is especially significant in this sample of students. (Scheuring and Thompson, 2024)

The finding is consistent with Human Capital Theory as ideas, skills and knowledge - cognitive and communication capacities - are a productive resource which can be enhanced through training and learning (Becker 1964). It also fits the rationale of Signalling Theory, which holds that cognitive expression and language competence can be assessed via interviews,

presentations, group activity, and written communication, and are important when employers are limited in the amount of information they have to go on when making decisions about a graduate's underlying competence (Spence, 1973; Anderson and Tomlinson, 2021). (Healy, 2023)

The second most important predictor is Language Proficiency ($\beta = 0.305$). The finding bolsters the thesis that communication is a graduate attribute and not just another. It is the medium in which knowledge and reasoning can be converted into effective organizational output. While a graduate may be technically competent, if he or she cannot explain a proposal, join a discussion or adjust the plan of communication to diverse audiences, he or she may have a problem translating the competence into work-related outcomes. (Scandurra et al., 2024)

There is an also highly significant relationship between Artificial Intelligence and Employability Skills ($\beta = 0.160$). It's not about the "size of the coefficient," though, since AI is still relevant. Rather, when other predictors are held constant, AI accounts for a smaller portion of the variance within this model than does Cognitive Expression and Language Proficiency. This aligns with recent studies that suggest that AI literacy is most effective when it is part of an extended, digital, cognitive, and interpersonal competence (Biagini, 2025; Daniel, 2025). (Abbas, Jam and Khan, 2024; Shahzad, Xu and Javed, 2024)

The model explains 55.1% of the variance in Employability Skills and has a meaningful explanatory power with 44.9% of the variation attributed to other factors that are not included in the model. The unexplained part of the analysis is theoretically important as it is conceivable that internships, work experience, social capital, career identity, personalities, disciplinary knowledge, labour market conditions, institutional opportunities and others can affect employability as well (Suleman, 2021).

The results continue to emphasize the need for an holistic strategy with regards to AI-powered education. A recent study by Luo et al. (2025) found that AI-driven learning tools can support personalised learning and feedback, yet the educational benefits rely on the instructional design and assessment practices, as well as on the effective pedagogical integration. Liang, Stephens and Brown (2025) further found that a good pedagogical integration of AI-learning tools is a crucial condition for educational benefits. Universities must not, however, be seen as offering the alternative to human communication and reasoning in the context of adopting AI. The present findings, however, are more in line with a complementary method of developing AI

capability in tandem with language competence and cognitive expression. (Jo, 2024; Luo et al., 2025)

8. Theoretical Implications

The research builds on Human Capital Theory by identifying a new set of employability related human capital skill areas—AI literacy, communication skills and cognitive skills—as new "human capital skills" for the modern era. It also extends Signalling Theory to the context of AI-employability, emphasizing that skills need to be observable and verbalizable before they can be valued in the labour market. Social Cognitive Theory is used to understand how AI aided learning can support learning capability development by engaging in practice and feedback and the Technology Acceptance Model is used to understand why students might exhibit different levels of willingness to use AI. It can also be explained by the communicative competence theory, which suggests that although work is becoming more technologically mediated, language skills are still vital for helping individuals understand the world and interact with it.

9. Practical Implications

9.1 Implications for the Field of language teaching in higher education

The main takeaway is that training for employability should not be solely focused on adopting AI. It is important to design curriculum units that include integrated learning activities where students are expected to use AI to conduct real-world tasks and to evaluate the AI-generated output, explain their choices, and convey their results in a professional manner. (Bradley, Priego-Hernández and Quigley, 2022; Healy, 2023)

Because Cognitive Expression is the best predictor, universities should include activities that involve students in analysing a problem, considering alternatives, justifying positions, and presenting evidence. These cognitive abilities can be made observable and assessable with the help of case studies, problem based learning, debates, executive summaries, and structured presentations. (Barta et al., 2022; Scheuring and Thompson, 2024)

Language development should likewise be connected directly to workplace situations. Instead of teaching language in isolation of and without regard to the students' overall competence, business correspondence, client interaction, negotiation, cross-cultural communication and interviews can be integrated into instruction.

9.2 Impact of AI on teaching and learning.9.4 The effect of AI on teaching and learning.

AI should be used as a tool to guide learning instead of creating students' work. Students may record prompts, evaluate and correct AI-generated responses, and edit AI-produced content independently based on their faculty's feedback. These practices can foster AI literacy beyond just a basic understanding to critical and responsible use. Baig and Yadegaridehkordi (2025); Shata and Hartley (2025)

The implications for employers and employability services are outlined below. The implications for employers and employability services are as follows:

Employers and career services can collaboratively create realistic assessments for the use and reasoning and communication with AI. Students can be given the chance to showcase skills through mock interviews, business case activity with AI support, presentations, portfolio review, and work simulations instead of a résumé. (Perez-Encinas and Berbegal-Mirabent, 2023)

9.3 Implications for faculty development

At least the following aspects of faculty development should be addressed: AI literacy, redesign of assessments, prompt assessment, academic-integrity procedures, and strategies to teach students to be critical consumers of AI output. The focus will still be on enhancing pedagogical competence and not just on using the technology for the sake of it.

10. Restrictions and potential development work.

There are some caveats to be noted. First, the cross-sectional design does not allow for causal statements to be made and does not account for whether AI, Cognitive Expression, and Language Proficiency result in gains in employability over time. In addition, the study relies on self-report scales, which could be affected by response style and discrepancies between the way participants self-actualize their competencies, especially for AI literacy. Third, they did not measure factors such as internships, work experience, social capital, and academic performance in the model (Suleman, 2021).

11. Conclusion

The study reveals that Employability Skills has a significantly and positively relationship with Artificial Intelligence, Cognitive Expression and Language Proficiency. The three predictors explain 55.1% of the variance in employability outcomes based on 202 students. Cognitive

Expression has the highest impact, then Language Proficiency and Artificial Intelligence, with these factors reflecting the importance of critical thinking, clear expression, communication and technological ability.

The results show that employability in today's work environment is not solely about the use of AI skills; it is about using AI with cognitive and communication skills. Higher education institutions need, therefore, to adopt a balanced approach where students can develop AI literacy while also being able to enhance reasoning, expression, and language skills in hands-on, industry-specific learning experiences. The study gives empirical evidence for integrated employability development and implications for curriculum planning, skill enhancement and graduate readiness. This study can be further extended in future by conducting multi-institutional, longitudinal and performance-based research.

References

1. Shata, A. and Hartley, K. (2025) 'Artificial intelligence and communication technologies in academia: faculty perceptions and the adoption of generative AI', *International Journal of Educational Technology in Higher Education*, 22, 14. <https://doi.org/10.1186/s41239-025-00511-7>.
2. Shahzad, M.F., Xu, S. and Javed, I. (2024) 'ChatGPT awareness, acceptance, and adoption in higher education: the role of trust as a cornerstone', *International Journal of Educational Technology in Higher Education*, 21, 46. <https://doi.org/10.1186/s41239-024-00478-x>.
3. Scheuring, F. and Thompson, J. (2024) 'Enhancing graduate employability – exploring the influence of experiential simulation learning on life skill development', *Studies in Higher Education*, 50(2), pp. 256–270. <https://doi.org/10.1080/03075079.2024.2334837>.
4. Scandurra, R., Kelly, D., Fusaro, S., Cefalo, R. and Hermannsson, K. (2024) 'Do employability programmes in higher education improve skills and labour market outcomes? A systematic review of academic literature', *Studies in Higher Education*, 49(8), pp. 1381–1396. <https://doi.org/10.1080/03075079.2023.2265425>.
5. Perez-Encinas, A. and Berbegal-Mirabent, J. (2023) 'Who gets a job sooner? Results from a national survey of master's graduates', *Studies in Higher Education*, 48(1), pp. 174–188. <https://doi.org/10.1080/03075079.2021.2021427>.

6. Luo, J., Zheng, C., Yin, J. and Teo, H.H. (2025) 'Design and assessment of AI-based learning tools in higher education: a systematic review', *International Journal of Educational Technology in Higher Education*, 22, 42. <https://doi.org/10.1186/s41239-025-00540-2>.
7. Kim, Y.A., Kim, K.A. and Tzokas, N. (2022) 'Entrepreneurial universities and the effect of the types of vocational education and internships on graduates' employability', *Studies in Higher Education*, 47(5), pp. 1000–1009. <https://doi.org/10.1080/03075079.2022.2055324>.
8. Karaca-Atik, A., Meeuwisse, M., Gorgievski, M.J. and Smeets, G. (2023) 'Uncovering important 21st-century skills for sustainable career development of social sciences graduates: a systematic review', *Educational Research Review*, 39, 100528. <https://doi.org/10.1016/j.edurev.2023.100528>.
9. Jo, H. (2024) 'From concerns to benefits: a comprehensive study of ChatGPT usage in education', *International Journal of Educational Technology in Higher Education*, 21, 35. <https://doi.org/10.1186/s41239-024-00471-4>.
10. Healy, M., Hammer, S. and McIlveen, P. (2022) 'Mapping graduate employability and career development in higher education research: a citation network analysis', *Studies in Higher Education*, 47(4), pp. 799–812. <https://doi.org/10.1080/03075079.2020.1804851>.
11. Healy, M. (2023) 'Careers and employability learning: pedagogical principles for higher education', *Studies in Higher Education*, 48(8), pp. 1303–1314. <https://doi.org/10.1080/03075079.2023.2196997>.
12. Delcker, J., Heil, J., Ifenthaler, D., Seufert, S. and Spirgi, L. (2024) 'First-year students AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education', *International Journal of Educational Technology in Higher Education*, 21, 18. <https://doi.org/10.1186/s41239-024-00452-7>.
13. Crompton, H. and Burke, D. (2023) 'Artificial intelligence in higher education: the state of the field', *International Journal of Educational Technology in Higher Education*, 20, 22. <https://doi.org/10.1186/s41239-023-00392-8>.
14. Chan, C.K.Y. and Hu, W. (2023) 'Students' voices on generative AI: perceptions, benefits, and challenges in higher education', *International Journal of Educational Technology in Higher Education*, 20, 43. <https://doi.org/10.1186/s41239-023-00411-8>.
15. Byrne, C. (2022) 'What determines perceived graduate employability? Exploring the effects of personal characteristics, academic achievements and graduate skills in a

- survey experiment', *Studies in Higher Education*, 47(1), pp. 159–176.
<https://doi.org/10.1080/03075079.2020.1735329>.
16. Bradley, A., Priego-Hernández, J. and Quigley, M. (2022) 'Evaluating the efficacy of embedding employability into a second-year undergraduate module', *Studies in Higher Education*, 47(11), pp. 2161–2173. <https://doi.org/10.1080/03075079.2021.2017676>.
17. Bond, M., Khosravi, H., De Laat, M. et al. (2024) 'A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour', *International Journal of Educational Technology in Higher Education*, 21, 4. <https://doi.org/10.1186/s41239-023-00436-z>.
18. Baig, M.I. and Yadegaridehkordi, E. (2025) 'Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education', *International Journal of Educational Technology in Higher Education*, 22, 5. <https://doi.org/10.1186/s41239-025-00506-4>.
19. Barta, A., Fodor, L.-A., Tamas, B. and Szamoskozi, I. (2022) 'The development of students' critical thinking abilities and dispositions through the concept mapping learning method – A meta-analysis', *Educational Research Review*, 37, 100481. <https://doi.org/10.1016/j.edurev.2022.100481>.
20. Abbas, M., Jam, F.A. and Khan, T.I. (2024) 'Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students', *International Journal of Educational Technology in Higher Education*, 21, 10. <https://doi.org/10.1186/s41239-024-00444-7>.
21. Anderson, V. and Tomlinson, M. (2021) 'Signaling standout graduate employability: the employer perspective', *Human Resource Management Journal*, 31(3), pp. 675–693. <https://doi.org/10.1111/1748-8583.12334>.
22. Bandura, A. (1986) *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice-Hall.
23. Becker, G.S. (1964) *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. New York: Columbia University Press.
24. Biagini, G. (2025) 'Towards an AI-Literate Future: A Systematic Literature Review Exploring Education, Ethics, and Applications', *International Journal of Artificial Intelligence in Education*, 35, pp. 2616–2666. <https://doi.org/10.1007/s40593-025-00466-w>.
25. Canale, M. and Swain, M. (1980) 'Theoretical bases of communicative approaches to second language teaching and testing', *Applied Linguistics*, 1(1), pp. 1–47.

26. Daniel, K. (2025) 'Can Generative AI Revolutionise Academic Skills Development in Higher Education? A Systematic Literature Review', *European Journal of Education*, 60(1), e70036. <https://doi.org/10.1111/ejed.70036>.
27. Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS Quarterly*, 13(3), pp. 319–340.
28. Hymes, D. (1972) 'On communicative competence', in Pride, J.B. and Holmes, J. (eds.) *Sociolinguistics: Selected Readings*. Harmondsworth: Penguin, pp. 269–293.
29. Liang, J., Stephens, J.M. and Brown, G.T.L. (2025) 'A systematic review of the early impact of artificial intelligence on higher education curriculum, instruction, and assessment', *Frontiers in Education*, 10, 1522841. <https://doi.org/10.3389/feduc.2025.1522841>.
30. Lintner, T. (2024) 'A systematic review of AI literacy scales', *Educational and Information Technologies*. [Use the final bibliographic details from the publisher database before submission.]
31. Luo, J., Zheng, C., Yin, J. and Teo, H.H. (2025) 'Design and assessment of AI-based learning tools in higher education: a systematic review', *International Journal of Educational Technology in Higher Education*, 22, 42. <https://doi.org/10.1186/s41239-025-00540-2>.
32. Spence, M. (1973) 'Job market signaling', *Quarterly Journal of Economics*, 87(3), pp. 355–374.
33. Suleman, F. (2021) 'Revisiting the concept of employability through economic theories: contributions, limitations and policy implications', *Higher Education Quarterly*, 75(4), pp. 548–561. <https://doi.org/10.1111/hequ.12320>.
34. Zhang, S., Prasad, P.G. and Schroeder, N.L. (2025) 'Learning About AI: A Systematic Review of Reviews on AI Literacy', *Journal of Educational Computing Research*. <https://doi.org/10.1177/07356331251342081>.
35. 'How AI literacy correlates with affective, behavioral, cognitive and contextual variables: A systematic review' (2025) *Computers and Education: Artificial Intelligence*, 9, 100493. <https://doi.org/10.1016/j.caeai.2025.100493>.
36. Salido, A., Syarif, I., Sitepu, M. S., Wana, P. R., Taufika, R., & Melisa, R. (2025). Integrating critical thinking and artificial intelligence in higher education: A bibliometric and systematic review of skills and strategies. *Social Sciences & Humanities Open*, 12, 101924.

37. Aditya, D., Silvestri, K., & Otermans, P. C. J. (2024). Can AI teach me employability? A multi-national study in three countries. *Frontiers in Artificial Intelligence*, 7, 1461158. <https://doi.org/10.3389/frai.2024.1461158>
38. Chen, S., & Cheung, A. C. K. (2025). Effect of generative artificial intelligence on university students learning outcomes: A systematic review and meta-analysis. *Educational Research Review*, 100737. <https://doi.org/10.1016/j.edurev.2025.100737>
39. Portocarrero Ramos, H. C., Cruz Caro, O., Sánchez Bardales, E., Quiñones Huatangari, L., Campos Trigoso, J. A., Maicelo Guevara, J. L., & Chávez Santos, R. (2025). Artificial intelligence skills and their impact on the employability of university graduates. *Frontiers in Artificial Intelligence*, 8, 1629320. <https://doi.org/10.3389/frai.2025.1629320>
40. Drydak, N. (2025). The formation of AI Capital in higher education: Enhancing students' academic performance and employment rates. *Computers and Education: Artificial Intelligence*, 100476.
41. Loyalka, P., Mistree, D., Fairlie, R., & Khanna, S. (2025). Job training, English language skills, and employability: Evidence from an experiment in urban India. *Economic Development and Cultural Change*, 73(4), 2131–2156. <https://doi.org/10.1086/734458>
42. Wana, P. R., Taufika, R., & Melisa, R. (2025). Integrating critical thinking and artificial intelligence in higher education: A bibliometric and systematic review of skills and strategies. *Social Sciences & Humanities Open*, 12, 101924. <https://doi.org/10.1016/j.ssaho.2025.101924>
43. Wut, T. M. E., Chan, A. H. E., Wong, S. M. H., & Chan, J. K. Y. (2025). Perceived artificial intelligence literacy and employability of university students. *Education + Training*, 67(2), 258–274. <https://doi.org/10.1108/ET-06-2024-0272>
44. *Computers and Education: Artificial Intelligence*, 9, 100476 (2025), “The formation of AI Capital in higher education: Enhancing students' academic performance and employment rates.” <https://doi.org/10.1016/j.caeai.2025.100476>
45. Ahmad, Z., Sultana, A., Abdul Latheef, N., Siby, N., Sellami, A., & Abbasi, S. A. (2025). Measuring students' AI competence: Development and validation of a multidimensional scale integrating educational psychology perspectives. *Acta Psychologica*, 259, 105446. <https://doi.org/10.1016/j.actpsy.2025.105446>
46. Adam, M., Yalley, C. E., & Poatob, S. (2025). Analysis of employability skills gaps among Bachelor of Arts social studies education students at the University of

Education, Winneba. *Discover Global Society*, 3, 112. <https://doi.org/10.1007/s44282-025-00248-8>

47. Miller, A., et al. (2024). An interdisciplinary assessment of information literacy instruction. *The Journal of Academic Librarianship*, 50(5), 102944. <https://doi.org/10.1016/j.acalib.2024.102944>
48. Wahab, S. A., et al. (2024). Graduate employability: A bibliometric analysis. *Global Business and Organizational Excellence*. <https://doi.org/10.1002/joe.22267>
49. Wut, T. M., Chan, E. A.-h., Wong, H. S.-m., & Chan, J. K. Y. (2025). Perceived artificial intelligence literacy and employability of university students. *Education + Training*, 67(2), 258–274. <https://doi.org/10.1108/ET-06-2024-0272>
50. Wynekoop, J., & Nakatani, K. (2024). Critical thinking skills for computing professionals: Closing the education–industry gap. *Industry and Higher Education*, 38(4). <https://doi.org/10.1177/09504222231221530>