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From Technical Competence to Communication Competence: The Mediating Role of Social Competencies in AI-Supported Academic Research

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Abstract

The increasing integration of artificial intelligence (AI) tools in higher education has transformed students' approaches to conducting academic research, emphasizing the importance of competencies that support effective AI-assisted research practices. Grounded in the Student Online Learning Readiness (SOLR) framework, this study examines the mediating role of social competencies in the relationship between technical competence and communication competence in students' use of AI tools for academic research tasks. A quantitative cross-sectional survey was conducted among 342 university students, and the data were analysed using structural equation modelling (SEM). The findings indicate that technical competence significantly predicts both social competence with instructors and social competence with classmates. In turn, these social competencies significantly influence communication competence. However, the direct relationship between technical competence and communication competence was not statistically significant. Bootstrapping analysis further confirmed that social competencies fully mediate the relationship between technical competence and communication competence. These results suggest that technical skills alone are insufficient for developing effective communication abilities when students use AI tools for academic research. Rather, communication competence emerges through meaningful interaction and collaboration with instructors and peers. The study contributes to the literature on AI-supported learning by highlighting the critical role of social competencies in transforming students' technical readiness into effective communication competence within AI-enhanced academic research environments.

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Introduction

The use of artificial intelligence (AI) tools, especially generative AI systems such as ChatGPT, Claude, and Gemini, is transforming the landscape of higher education and academic research (Kurtz et al., 2024). These tools have evolved from being mere technological aids to becoming research assistants for university students (Baha et al., 2023; Sanz-Tejeda et al., 2026). University students are increasingly relying on these tools to meet the requirements for conducting academic research (Kurtz et al., 2024; Sanz-Tejeda et al., 2026). The functions that these AI platforms perform, enable students to more efficiently synthesize information from large data sets, indicating changes in the research processes of these university students (Al-Bukhrani et al., 2025; Arroyo-Machado et al., 2025; Garcia, 2025). This rapid evolution of technology has highlighted the importance of understanding the essential competences needed for students to effectively and responsibly utilize AI-supported research environments (Adamakis & Rachiotis, 2025).

With the increasing integration of AI into the academic cycle, students' interactional competencies should be a primary concern for higher education institutions (Al-Hattami, 2025; Sustaningrum & Haldaka, 2025). Simply having technical access or knowing how to use software is not sufficient to effectively engage in AI-supported research (Zhao et al., 2025). Due to the way generative AI systems function through conversational and iterative exchanges, the quality of academic outcomes depends on students' abilities to communicate, collaborate, and critically appraise AI outputs (Hao et al., 2025; Ren et al., 2025). Beyond finding information, research competencies encompass understanding how to use digital interfaces, formulating effective prompts for AI systems, as well as understanding the social and ethical implications of utilizing AI within academic environments (Hughes et al., 2025; Lemke et al., 2023; Rahman et al., 2025). Therefore, it is vital for universities to find all of the factors that contribute to the readiness of students to effectively utilize these AI systems and tools to assist students with their academic work (Sallai et al., 2024; Schmidt et al., 2025).

Yu and Richardson's (2015) framework of Student Online Learning Readiness (SOLR) allows for the examination of the competencies within the framework. The SOLR framework focuses upon four dimensions of students' readiness to learn with the use of technologies:

- The first is technical competence, which involves the ability to operate digital devices and navigate online learning spaces.
- The second is social competence with the instructor, which refers to the ability to ask for help and communicate with a lecturer in digital spaces.
- Next is social competence with classmates, which describes the ability to work together and pool knowledge with learning partners.
- The last is communication competence, which involves the ability to express thoughts and ideas clearly and effectively in online formats (Yu, 2018; Yu & Richardson, 2015).

These skills are increasingly recognized as important predictors of student success in a growing range of digital environments, as they determine how effectively individuals engage with the technical, interpersonal, and communicative aspects of contemporary higher education (Chien et al., 2022; Liu, 2019).

Another challenge concerning the SOLR components related to AI-assisted research is the lack of connection between its components (Mogaji et al., 2024; Zhao et al., 2025). Experts in the field have indicated that being skilled in the technical aspects of AI components is not enough to convince students to use these tools. Their research proves that the advanced communication skills required to perform high-end research cannot be obtained simply by using these AI tools (Knoth et al., 2024; Ren et al., 2025; Federiakin et al., 2024). Instead, the communication competence is often developed through social interaction and group learning (Ramakrishnan et al., 2024; Wang et al., 2022). Students learn to enhance their communication of research by observing peers' strategies, engaging in collaborative prompting, and receiving instructor feedback about the ethical and rhetorical quality of their AI-assisted exchanges (Abdalla, 2024; Korchak et al., 2025; Wang & Gao, 2025). This indicates the existence of a mediated process whereby technical skills facilitate students' engagement with the social structures of the digital university, which in turn leads to the acquisition of higher forms of communication competence (Obadă et al., 2026; Ren et al., 2025; Wen et al., 2025).

Although these competencies are known to be important, there is no clear academic or descriptive literature (Alshammarı et al., 2025; Zhao et al., 2025). To date, previous studies using the SOLR framework have predominantly conceptualized the four competencies as four parallel and independent dimensions and investigated the contribution of each of them towards learning outcomes such as satisfaction or academic persistence (Chien et al., 2022; Yu, 2018). The focus has been on the structural relationships among these competencies or the possibility that they develop hierarchically or in a mediated way. Furthermore, while previous studies have seen the emergence of research on the determinants of AI adoption in higher education, only a handful of studies have explored how social interactional readiness acts as a mechanism that links students' technical competence to their communicative competence while using AI tools for academic research tasks (Alshammarı et al., 2025; Yakubu et al., 2025). If universities do not understand these mediating mechanisms, they risk implementing technical training initiatives that do not address the social and communicative skills necessary for meaningful engagement with AI in research (Lee & Chan, 2024).

The current study therefore aims to examine the mediation role of social competence with the instructor and social competence with classmates in the relationship between technical competence and communication competence regarding the use of AI tools for academic research by students. The study employs a two-step structural equation modelling (SEM) approach to test a structural model comprising technical readiness, communication competence, and students' capacity to socially engage with the academic community. The aim was to determine whether technical readiness directly translates to communication competence or not. Recent studies have observed that effective use of AI in academic research is achieved through peer learning and collaborative experimentation. Given the interactive nature of generative AI, such experimentation might become more pronounced (Jesus et al., 2024; Ke et al., 2025).

The findings of this study will benefit the literature on educational technology and student readiness in various ways. To begin, it expands the SOLR framework to the new context of AI-supported academic research to show how relevant it is in environments with advanced AI-based research assistants. In addition, it sheds light on the structural linkages among readiness competencies by going beyond parallel measurement to identifying the sequential pathways through which digital competencies develop.

The importance of social interactional competencies is also highlighted in the literature as mediating variables between the technical capabilities of AI tools and the more sophisticated forms of communication that are necessary for effective collaboration between humans and AI agents in the research process (Obadă et al., 2026; Ren et al., 2025; Wang & Gao, 2025). The findings of these research efforts also enable university administrators and instructors to take certain steps to better prepare students for the demands of conducting research in the age of AI. Overall, researchers emphasize the need to take a comprehensive approach to preparing students for AI-assisted research that takes into account both their technological and social competency developments.

Literature Review

Artificial Intelligence Tools in Higher Education

The educational landscape is undergoing rapid changes as a result of the emergence of generative AI tools, such as those with large language models like ChatGPT and Claude, or those that assist in performing research (Adamakis & Rachiotis, 2025; Kurtz et al., 2024). Studies by Baha et al. (2023) and Sanz-Tejeda et al. (2026) indicate that these tools are no longer limited to automating certain tasks for educators. Instead, students are utilizing these tools to accomplish more advanced research tasks, such as retrieving information from databases, summarizing the contents of academic sources, and formulating research frameworks for their own research projects (Kurtz et al., 2024; Sanz-Tejeda et al., 2026). In addition, tools such as AI writing assistants and research support have transformed practices in academic writing, from providing quick feedback, to enabling knowledge synthesis, and helping students make the leap from original ideas to full-blown academic text (Al-Bukhrani et al., 2025; Garcia, 2025).

The recent move towards AI-assisted research is causing a shift in the research paradigm in knowledge construction (Dai et al., 2026; Vieriu & Petrea, 2025). Instead of being passive consumers of information, students are increasingly co-constructing with AI to refine their research questions and make sense of large data sets (Hao et al., 2025; Ranade et al., 2024). However, these instruments also present challenges that require a rethink of pedagogical integrity and new digital literacies (Adamakis & Rachiotis, 2025; Schmidt et al., 2025). As a result, there is increasing recognition of the effective utilization of AI for academic purposes not simply as a technical capacity but as a combination of digital readiness and cognitive flexibility (Hughes et al., 2025; Sallai et al., 2024).

Students' Online Learning Readiness

Students require a high level of online learning readiness to successfully adapt to technology-rich learning environments (Chien et al., 2022). The SOLR framework was developed by Yu and Richardson. According to Yu and Richardson, competence is made up of four components: technical competence, social competence with academic staff, social competence with fellow students, and communication competence (Yu, 2018; Yu & Richardson, 2015). Technical competence relates to the individual's ability to use digital tools and learn online. Social competence relates to the individual's ability to form positive relationships with instructors and fellow students online, as well as to ask for help or to cooperate with others in the virtual classroom. Finally, communication competence relates to the individual's ability to communicate their ideas within the online classroom and environment, whether through language or rhetorical skills (Yu, 2018; Yu & Richardson, 2015).

These competencies collectively indicate the level of readiness that a student has to take part in the learning process. Numerous research studies have used the SOLR framework to measure the academic success and satisfaction levels of students in online courses. The research findings have indicated that students who are found to have a higher level of readiness usually have less stress and have fewer issues in preparing for online courses than students with lower levels of readiness (Chien et al., 2022; Liu, 2019). Furthermore, these competencies can assist researchers in understanding the level of technological competency that students have when they begin to engage in AI-enhanced research projects (Alshammari et al., 2025; Sudaryanto et al., 2023; Zhao et al., 2025).

Technical Competence in Digital and AI-Supported Learning

Technical competence is the first requirement for individuals to engage in the digital environment. Chien et al. (2022) define technical competence as the student's self-efficacy with tasks related to the digital environment, such as operating digital hardware and software, and overcoming technical difficulties encountered while using these digital platforms. The technical competence of students has been shown to reduce the technostress exhibited by students and increase the likelihood of successful adoption of technology by students (Alshammari et al., 2025; Liang et al., 2024). Furthermore, technical competence is an especially important component in incorporating artificial intelligence into the classroom, as students will be required to execute tasks that require technical skills to perform those steps (Alshammari et al., 2025).

According to both Sudaryanto et al. (2023) and Zhao et al. (2025), students with better technical skills tend to find AI tools to be both more useful and easier to use. Furthermore, technical skills allow students to devote their cognitive resources to learning rather than to resolving issues that relate to the technology (Feng et al., 2025; Liang et al., 2024). Technical skills in the use of various technologies allow students to utilize AI search engines, for instance, or other software that helps to organize the information that they intend to investigate with those AI tools (Delcker et al., 2024; Staddon, 2023). Thus, these technical skills enable students to investigate the educational capabilities of AI (Alshammari et al., 2025; Zhao et al., 2025).

Social Competencies in Online Learning Environments

Competence with instructors and competence with classmates are the second and third dimensions of the SOLR framework. They emphasize the interpersonal nature of technology-mediated learning environments (Yu, 2018; Yu & Richardson, 2015). The concept of 'social competence with instructors' refers to the capacity of students to clarify, engage in academic dialogue, and have professional relationships with faculty in a digital learning environment (Chien et al., 2022). In a scenario of AI acceptance, instructors often serve as the principal social influencer and guide to foster ethical and responsible AI usage (Thanomsing & Sharma, 2024). Evidence suggests that students who display high social competence towards their instructors proactively reach out to consult on the effective use of AI tools, leading to the more confident and ethically sound use of such tools in their research (Beckman et al., 2025; Zhao et al., 2025).

In the same way, 'social competence with classmates' refers to the capacity of students to work together, co-regulate, and develop supportive networks with peers when engaging in learning online (Yu & Richardson, 2015). Student–peer engagement management is considered key to the diffusion of new technologies. Students learn about the latest AI tools (such as ChatGPT) and various prompting techniques mainly through collaborative assignments and informal peer-to-peer exchanges (Abdalla, 2024; Feng et al., 2025; Korchak et al., 2025). By providing opportunities for the exchange of research approaches and AI-enabled insights, social competence with peers enhances the whole class's ability to use digital equipment effectively and creatively (Ke et al., 2025; Zapata et al., 2025).

Communication Competence in Digital Learning Contexts

Communication competence is one of the most critical skills in the era of generative AI (Knoth et al., 2024; Lee & Palmer, 2025; Federiakin et al., 2024). The concept refers to the capacity to express intricate research concepts and engaging in accurate and iterative discussions with human beings and AI (Kim et al., 2025; Knoth et al., 2024). In AI-assisted research contexts, the quality of the prompts given to AI largely determines the accuracy and relevance of the resulting scholarly output (Gibreel & Arpacı, 2025; Federiakin et al., 2024). This interaction process poses a rhetoric challenge that requires students to provide contextual information, set constraints, and assess the AI response logic (Ranade et al., 2024; Rodriguez-Donaire, 2024).

Research on AI literacy indicates that communication competence allows students to move from vague questioning to structuring prompt engineering as an academic skill (Knoth et al., 2024). Students who have better communication skills are more likely to critically and synthetically use the insights suggested by AI applications in their own academic productions while retaining ownership of their own insights (Kim et al., 2025). As AI interaction is increasingly conversational, students' ability to communicate in digital environments ultimately dictates whether AI is a useful agent that produces relevant research or a possible generator of misinformation (Knoth et al., 2024; Shata & Hartley, 2025).

The Mediating Role of Social Competencies

Theoretical and emerging empirical evidence suggests that social competencies may serve as critical mediators between students' technical competence and their advanced communication ability (Obada et al., 2026; Ren et al., 2025; Wang & Gao, 2025). While operational skills required to use digital tools are provided by technical competence, communication competence, especially in the research context, requires the development of linguistic and rhetorical skills, which are mostly acquired through social interaction and learning (Ramakrishnan et al., 2024; Wang et al., 2022). Students' social competence in interactions with instructors and classmates offers them a social environment where communicative skills can be practised and refined (Abdalla, 2024; Korchak et al., 2025).

Students with technical competence may be able to enter and participate in digital educational spaces in which they observe the instructor modelling and peers sharing strategies related to AI-assisted research practices (Ke et al., 2025; Luo et al., 2025; Staddon, 2023). The feedback mechanisms generated by these forms of social modelling teach students how to improve the way they communicate with AI systems (Jesus et al., 2024; Zapata et al., 2025). A student with the technical ability to engage in online discussion forums may be able to engage in exchanges about effective ways to prompt AI. Ultimately, this may help students to formulate clear research questions to large language models (Jesus et al., 2024; Ke et al., 2025; Korchak et al., 2025). In this sense, social competence could operate as a mediating variable, meaning that students' social competence could transform basic technological readiness in relation to high-tech communication competence (Obadă et al., 2026; Ren et al., 2025).

Research Gap and Hypothesis Development

Although the literature sufficiently recognizes the importance of the SOLR framework, to date studies have treated the dimensions as parallel constructs and largely focused on their individual predictive effects (Chien et al., 2022; Yu, 2018). The competencies of researchers concerning AI-assisted academic research have only been examined in limited studies (Razzouki et al., 2025; Zhao et al., 2025). The majority of studies on AI adoption and use in higher education relies on conventional technology acceptance frameworks such as the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), and similar models. Adopting these conventional frameworks often overlooks readiness-based pathways that can lead to the effective use of technology (Alshammarı et al., 2025; Yakubu et al., 2025).

The current study seeks to fill this gap by testing a structural mediation model that investigates how technical competence influences communication competence through the mediation of social competence with teachers and social competence with classmates. By exploring these sequentially related constructs, the study presents a more dynamic comprehension of how higher education environments are capable of producing AI-ready scholars.

Based on a synthesis of the reviewed literature, the following hypotheses have been proposed:

H1: Technical competence positively influences social competence with instructors.

H2: Technical competence positively influences social competence with classmates.

H3: Technical competence positively influences communication competence.

H4: Social competence with instructors positively influences communication competence.

H5: Social competence with classmates positively influences communication competence.

H6: Social competence with instructors mediates the relationship between technical competence and communication competence.

H7: Social competence with classmates mediates the relationship between technical competence and communication competence.

The proposed research model is presented below in Figure 1.

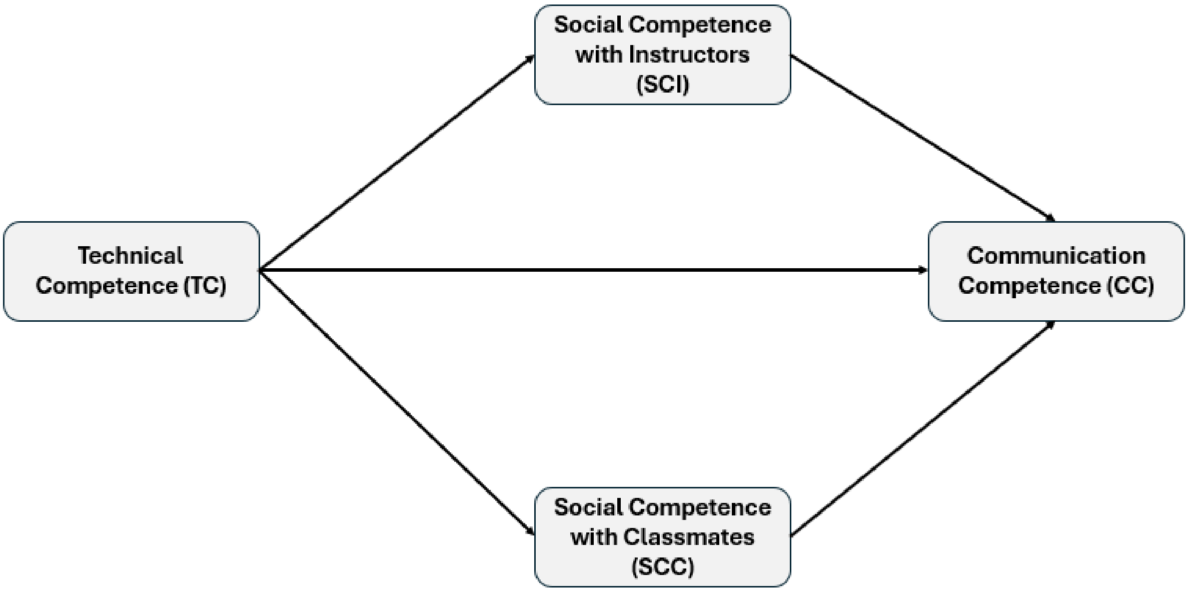

Figure 1. Proposed Research Model

Methodology

Research Design

The quantitative cross-sectional research design used in this study to describe the structural relationship among competencies was borrowed from the SOLR framework and applied in the context of students' use of AI tools for academic research tasks. A quantitative approach was deemed suitable because the study sought to test hypothesized relationships between latent constructs and examine the mediating role of social competencies in the relationship between technical competence and communication competence.

Structural equations modelling was used to achieve the research objectives, as this method allows for testing multiple relationships between latent variables while accounting for measurement error. The method is therefore appropriate for testing complex mediation models (Hair et al., 2019; Awang, 2015). A two-step SEM approach was utilized in this study. A sequence analysis was conducted by employing confirmatory factor analysis (CFA) to test the adequacy of the measurement model, and a structural model analysis was used to explore the hypothetical relationship. Thus, the model was analysed according to the theorem built.

Participants and Data Collection Procedures

The study participants consisted of 342 university students enrolled in higher education programmes. To recruit students participating in technology-facilitated learning environments and with experience of using AI tools for their academic activities, a convenience sampling strategy was used. According to Hair et al. (2019), a sample size of 200 observations meets the minimal threshold for SEM analysis, that is, the parameters are regarded as reliable.

Data were collected by means of a structured questionnaire, distributed online via Google Forms. The survey link was shared with the students using their official university email addresses. Moreover, the link was also posted on the Blackboard learning management system. Participation in the study was voluntary, and students were invited to complete the questionnaire at their convenience. The final dataset for analysis consisted of 342 valid responses.

Measurement Instrument

The instrument developed for the survey was based on the SOLR framework proposed by Yu and Richardson (2015). The SOLR model is widely utilized to assess students' readiness for technology-mediated learning environments. The model encompasses multiple competencies that complement the online learning experience and successful digital interaction.

The instrument measured four key competencies relevant to students' engagement with AI tools for academic research tasks:

- Technical competence (TC) – students' ability to effectively use digital technologies and online platforms.
- Social competence with instructors (SCI) – students' ability to interact and communicate with instructors in online learning environments.
- Social competence with classmates (SCC) – students' ability to collaborate and interact with peers in digital learning contexts.
- Communication competence (CC) – students' ability to express ideas clearly and participate in academic discussions within technology-supported environments.

We adapted the measurement items of validated SOLR scales from past studies. All the items were measured using five-point Likert scales, where 1 measures 'strongly disagree' and 5 measures 'strongly agree'. This type of scale was selected as it is widely used within the educational technology research community for assessing perceptions, attitudes, and competency assessments.

Data Analysis

We used SPSS and AMOS software for data analysis in two stages. SPSS was first used for the preliminary data screening and descriptive statistics analysis. Descriptive statistics were used to analyse the participants' demographic characteristics. As suggested by Hair et al. (2019) and Awang (2015), in the second stage, a two-step SEM analysis was conducted using AMOS. In the first step, we performed CFA of the measurement model. The examination of the standardized factor loadings, composite reliability (CR), and average variance extracted (AVE) establishes the reliability and validity of the constructs. Discriminant validity was examined using the Fornell–Larcker criterion, which states that the square root of each construct's AVE must be greater than the constructs' intercorrelations. Convergent validity across the scales was established through factor loadings and AVE which exceeded consensus thresholds. In the second step, we performed SEM to test the hypothesized relationships among the constructs and to examine the mediating role of social competencies in the effect of technical competence on communication competence. The structural model was assessed using various commonly reported model fit indices, such as the ratio of chi-square to degrees of freedom (χ^2/df), the comparative fit index (CFI), the Tucker–Lewis index (TLI), the incremental fit index (IFI), and the root mean square error of approximation (RMSEA).

The importance of mediation effects was evaluated by performing bootstrapping with 5,000 resamples. Bootstrapping is encouraged for mediation analysis to obtain indirect effects and confidence intervals without the effect of the normality assumption on the sampling distribution (Hair et al. 2019). As a result of this procedure, we were able to determine the significance of the indirect effects of technical competence on communication competence through social competencies. Using these analytical procedures, the study systematically examined the relationship between technical competence, social competence, and communication competence in terms of the participants' use of AI tools for academic research tasks.

Results

Demographic Profile of the Participants

A questionnaire was completed by a total of 342 university students. As indicated in Table 1, the respondents have various demographic characteristics. In terms of gender, the sample consisted of 216 female students (63.2%) and 126 male students (36.8%), meaning that female students comprised the majority of the sample. With regard to academic level, most participants were undergraduate students, namely 238 students (69.6%), while 104 participants (30.4%) were postgraduate students. The study findings are therefore mostly based on undergraduates' perceptions and skills, although postgraduates also represent a sizeable part of the sample.

Table 1. Demographic Characteristics of the Study Participants

Variable	Options	Frequency	Percent
Gender	Male	126	36.8
	Female	216	63.2
Academic levels	Undergraduate	238	69.6
	Postgraduate	104	30.4
Colleges	Education	95	27.8
	Business Administration	64	18.7
	Sharia and Law	42	12.3
	Arts	33	9.6
	Computer Science and Engineering	24	7.0
	Engineering	22	6.4
	Health Sciences	35	10.2
	Science	27	7.9
Total		342	100.0

Analysis of the academic disciplines of participants indicates that respondents were drawn from a range of colleges. The College of Education represents the largest percentage of respondents at 27.8%. This is followed by

Business Administration at 18.7% and Sharia and Law at 12.3%. The remainder of the participants were drawn from the College of Health Sciences (10.2%), the College of Arts (9.6%), the College of Science (7.9%), the College of Computer Science and Engineering (7.0%), and the College of Engineering (6.4%). The overall demographic distribution indicates that students from various fields and education levels participated in the study. This means that the sample is fairly representative and provides a wide variance of students' competencies related to the use of AI tools for academic research tasks.

Confirmatory Factor Analysis (CFA) and Measurement Model Validation

The adequacy of the measurement model and the construct validity of the latent variables were assessed using SEM with CFA, including the convergent and discriminant validity of the four latent constructs: technical competence (TC), social competence with instructors (SCI), social competence with classmates (SCC), and communication competence (CC). Based on the overall model fit indices, the measurement model exhibited an acceptable to good fit with the data. The study's results indicated $\chi^2/df = 3.565$, CFI = .952, TLI = .944, IFI = .952, NFI = .934, and RMSEA = .087. The SEM model fit is acceptable if the χ^2/df values are below 5.0, the CFI, TLI, IFI, and NFI values are above .90, and the RMSEA values are below .08–.10 (Awang, 2015; Hair et al., 2019). To summarize, the measurement model shows that the construct validity is satisfactory, that is, it confirms that the indicators are valid and represent the latent constructs. Figure 2 presents the CFA measurement model.

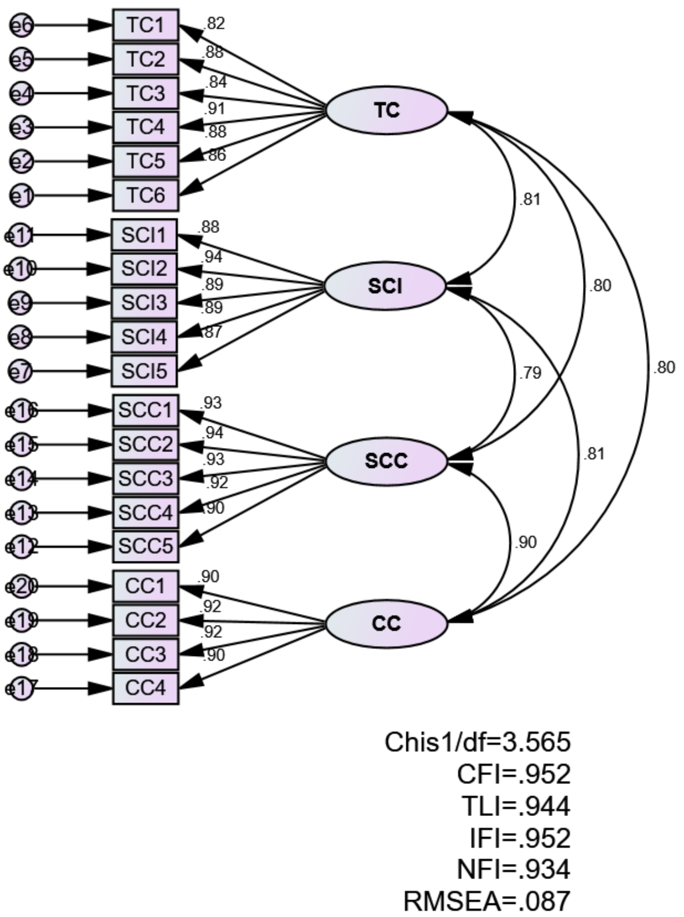

Figure 2. Confirmatory Factor Analysis Measurement Model

Assessment of convergent validity was conducted using CR and AVE. The results presented in Table 2 indicate that all the constructs surpassed the threshold values. All the values of CR (>0.70) and AVE (>0.50) met the threshold values as suggested by previous researchers (Awang, 2015; Hair et al., 2019). Specifically, the CR values varied from 0.947 to 0.967 and AVE values from 0.749 to 0.856 across the constructs (SCC: CR = 0.967, AVE = 0.856; TC: CR = 0.947, AVE = 0.749; SCI: CR = 0.953, AVE = 0.801; CC: CR = 0.952, AVE = 0.832). Values above the suggested thresholds mean the measurement items converge strongly, which establishes convergent validity.

Table 2. Composite Reliability and Convergent Validity of the Measurement Constructs

Constructs	**CR**	**AVE**
SCC	0.967	0.856
TC	0.947	0.749
SCI	0.953	0.801
CC	0.952	0.832

Next, discriminant validity was tested to ensure that the latent constructs were empirically distinct. Discriminant validity refers to the extent to which a measure deviates from other measures that assess different constructs. According to the Fornell–Larcker criterion, discriminant validity is established if the square root of the AVE of each construct is greater than the correlations of that construct with the other constructs in the model (Fornell & Larcker, 1981; Awang, 2015; Hair et al., 2019).

Table 3 presents the diagonal values, which reflect the square root of the respective AVEs, which were found to be 0.925 for SCC, 0.866 for TC, 0.895 for SCI, and 0.912 for CC. Moreover, each of the values is greater than their respective inter-construct correlation. In addition, the maximum shared variance (MSV) values for all the constructs were less than their respective AVE values, thus supporting discriminant validity. These findings provide evidence that each construct is a distinct conceptual domain and that the measurement items are more strongly correlated with the construct to which they were assigned than any other construct in the model. The results therefore present credible evidence that discriminant validity was achieved for all latent constructs of the measuring model.

Table 3. Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Constructs	**MSV**	**MaxR(H)**	**SCC**	**TC**	**SCI**	**CC**
SCC	0.810	0.969	0.925			
TC	0.653	0.950	0.799	0.866		
SCI	0.653	0.956	0.794	0.808	0.895	
CC	0.810	0.953	0.900	0.802	0.808	0.912

Structural Model and Standardized Estimates

The estimation of the structural model was calculated with the standardized estimates used to evaluate the strength of the relationship among the latent constructs. The measurement item loadings on the respective latent constructs,

It is common to evaluate standardized estimates to assess whether the indicators are adequate representations of their corresponding latent variables (measurement model), and to interpret the size of the structural relationships (structural model) involved in the study. The outcomes of the study showed that on their respective constructs all measurement items loaded good with standardized factor loadings above 0.50. Based on the guidelines for SEM, values above 0.50 are acceptable, while a value above 0.70 is a strong indicator of reliability (Awang, 2015; Hair et al., 2019). These results confirm that the observed indicators truly measure the corresponding latent constructs.

The coefficient of determination (R^2) was used for the endogenous construct to confirm specification linearity and explanatory power in addition to the factor loadings. The results showed that communication competence (CC) produced an R^2 value of .83, which shows that the predictor accounted for 83% of the variance in CC. This value indicates a strong level of explanatory power, such that the proposed structural relationships strongly explain the dependent construct in question. According to Cohen (2013), ideal R^2 values that denote a large effect size are 0.26 or higher, whereas 0.13 and 0.02, respectively, denote medium and small effect sizes. In the present study, the empirical analysis results yielded an R^2 coefficient of 0.83, which indicates that the structural model is robust and can explain the communication competence of students in the proposed framework. Figure 3 presents the output of the structural model with standardized path coefficients.

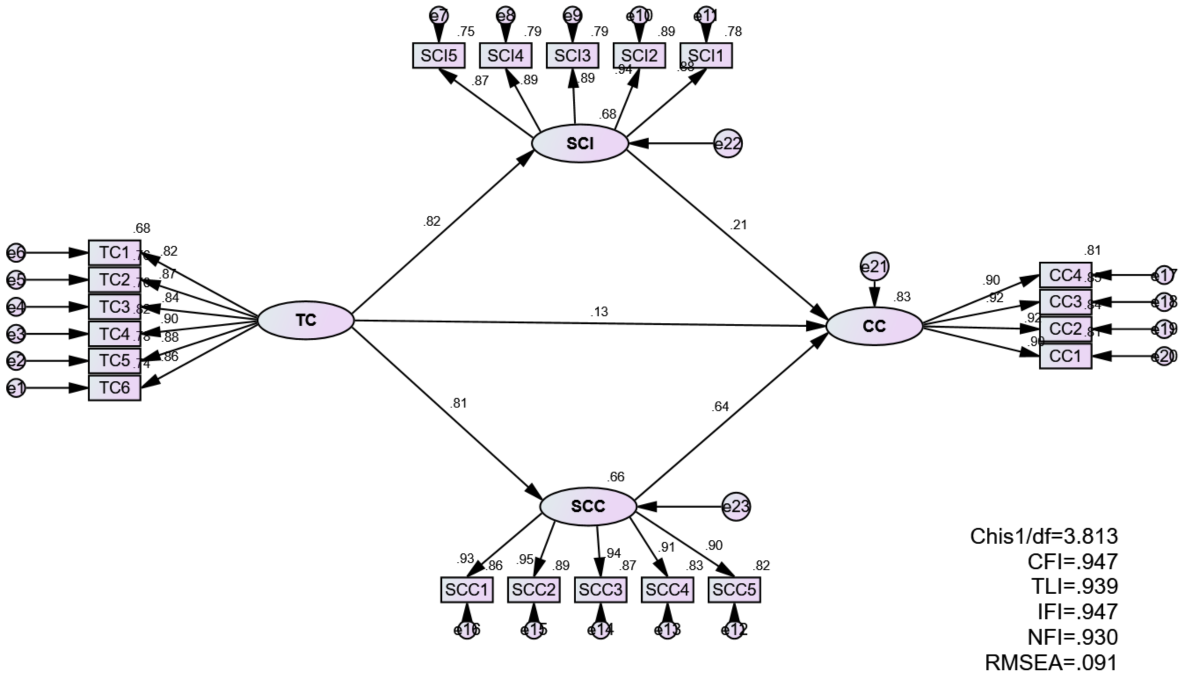

Figure 3. Structural Model with Standardized Path Coefficients

Unstandardized Estimates

Based on the results, the structural relationships among the latent constructs were tested by examining the unstandardized estimates to test the research hypotheses in addition to determining their statistical significance.

The unstandardized estimates in SEM are the actual (β values) regression coefficients. These coefficients refer to the size, meaning, and direction of relationships between constructs. These are subsequently used to formulate the critical ratio (CR), which is obtained from the ratio of the parameter estimate to the standard error. The critical ratio is like a *t*-value that indicates whether the estimated parameter is statistically significant or not.

According to the SEM standards, a CR value greater than ±1.96 is statistically significant at the 0.05 level, such that it supports the proposed hypothesis (Awang, 2015). The unstandardized estimates were therefore examined to evaluate the true regression coefficients (β) and to assess whether the expected relationships among the constructs are supported. This process allowed the hypotheses to be tested directly by looking at both the significance and direction of the structural paths in the model. Paths with significant CR values offer empirical support for their associated hypotheses, while paths with non-significant CR values indicate the rejection of hypotheses. Figure 4 presents the output of the structural model with unstandardized path estimates.

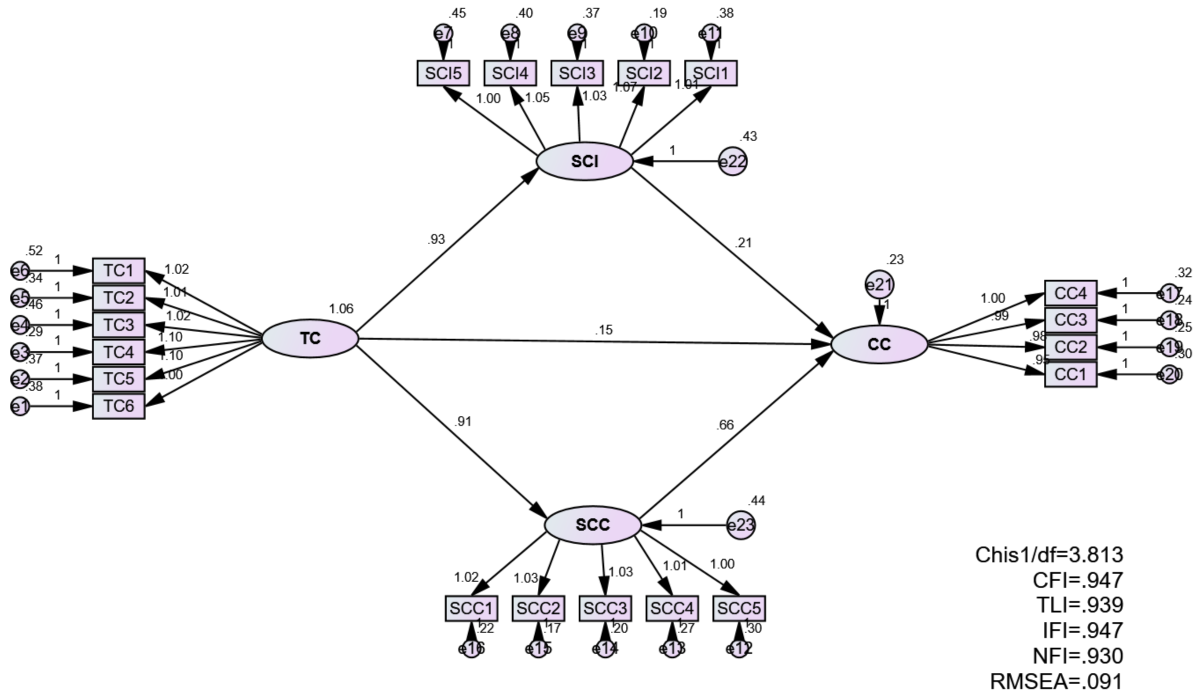

Figure 4. Structural Model with Unstandardized Path Estimates

Results of Hypothesis Testing

Structural relationships among the latent constructs were explored with the unstandardized regression estimates of the SEM. The hypotheses were assessed using the critical ratio and relevant *p*-values. In SEM analysis, the critical ratio is used to assess the significance of a path. As shown in Table 4, the results indicate that technical competence (TC) has a significant positive effect on social competence with instructors (SCI) (β = 0.929, critical ratio = 16.547, $p < .001$). This finding provides strong empirical support for H1, suggesting that students with higher levels of TC are more capable of interacting effectively with instructors in online learning environments.

Similarly, TC was found to significantly and positively influence social competence with classmates (SCC) (β =

0.909, critical ratio = 17.140, $p < .001$). Therefore, H2 is supported, suggesting that students with stronger TC are better able to engage in collaborative and social interactions with their peers in online academic contexts. Regarding the direct effect of TC on communication competence (CC), the results show that TC has a positive but statistically non-significant effect on CC (β = 0.149, critical ratio = 1.870, $p = .062$). Since the *p*-value exceeds the recommended threshold of .05, H3 is not supported. This finding suggests that TC alone may not directly enhance students' CC.

Furthermore, social competence with instructors (SCI) was found to significantly and positively influence CC (β = 0.210, critical ratio = 3.941, $p < .001$). Consequently, H4 is supported, suggesting that students who demonstrate stronger social competence in their interactions with instructors tend to exhibit higher levels of CC. Likewise, social competence with classmates (SCC) has a significant positive effect on CC (β = 0.660, critical ratio = 11.875, $p < .001$). This result supports H5, suggesting that effective peer interaction plays a substantial role in enhancing students' CC within online learning environments. Overall, the findings indicate that while TC strongly predicts students' social competencies, CC is primarily shaped by students' ability to interact socially with instructors and classmates, highlighting the importance of social engagement in the development of CC within the SOLR framework.

Table 4. Structural Model Results and Hypothesis Testing

			Estimate	S.E.	C.R.	P	Results
SCI	<---	TC	.929	.056	16.547	***	Significant
SCC	<---	TC	.909	.053	17.140	***	Significant
CC	<---	SCI	.210	.053	3.941	***	Significant
CC	<---	SCC	.660	.056	11.875	***	Significant
CC	<---	TC	.149	.079	1.870	.062	Not Significant

Mediation Analysis Using Bootstrapping

The bootstrapping procedure was performed to review the mediating roles of social competence with instructors and social competence with classmates in the relationship between technical competence and communication competence. Bootstrapping is a preferred method in mediation analysis, as it does not require the sampling distribution to be normally distributed. Additionally, it provides more robust estimates of indirect effects (Hair et al., 2022; Preacher & Hayes, 2008).

As shown in Table 5, the results indicate that the direct effect of TC on CC was not statistically significant (β = 0.149, $p = 0.204$). This finding suggests that TC alone does not directly predict students' CC. However, the indirect effects through the mediating variables were statistically significant. Specifically, the indirect path TC → SCI → CC was significant (β = 0.195, $p < .001$), indicating that social competence with instructors mediates the relationship between TC and CC. Therefore, H6 is supported. This finding suggests that students with higher levels of TC are better at interacting with instructors in online learning environments, which subsequently enhances their *CC*. Similarly, the indirect path TC → SCC → CC was also statistically significant (β = 0.600, *p*

< .001). This result provides strong support for H7, suggesting that social competence with classmates significantly mediates the relationship between TC and CC. In other words, students with stronger TC tend to interact more effectively with their peers, which in turn improves their CC.

Moreover, the total indirect effect of TC on CC was significant ($\beta = 0.795$, $p < .001$), suggesting that the influence of TC on CC occurs primarily through the social competence constructs. Given that the direct effect of TC on CC is non-significant while the indirect effects are significant, the results indicate full mediation through both SCI and SCC. These findings highlight the critical role of social interaction competencies in translating students' technical abilities into effective CC within the online learning context.

Table 5. Results of Mediation Analysis

Path	**Estimate**	**p-value**	**Result**	**Mediation Type**
TC → CC	0.149	0.204	Not Significant	—
TC → SCI → CC	0.195	< .001	Significant	Full mediation
TC → SCC → CC	0.600	< .001	Significant	Full mediation
TC → CC (Total indirect)	0.795	< .001	Significant	—

Discussion

The present study evaluated the structural relationships of the dimensions of the Student Online Learning Readiness framework in the context AI-assisted academic research. Based on an SEM analysis of data from 342 university students, several key pathways became evident, indicating how students progress from basic technical skills to advanced communication skills when using AI tools. The findings reveal that technical competence is a significant predictor of social competence with teachers and peers. As a result, both social competence dimensions have a significant positive impact on communication competence. The effect of technical competence on communication competence is reported as not significant. By contrast, the bootstrapping analysis revealed that social competencies fully mediate the relationship. It seems technical skills are essential but not enough to initiate suitable research-oriented communication with AI tools. Instead, developing this competence seems to be a function of socialization and collaboration within a community (Alshammarı et al., 2025; Zhao et al., 2025).

A critical relationship exists between technical competence and social competencies, with technical self-efficacy facilitating digital interaction at the foundation. According to the findings of Ren et al. (2025) and Sudaryanto et al. (2023), a student with technical skills has a lighter load on their cognitive processes within technological environments. These decreases in technicalities for students allow for their cognitive processes to be dedicated to more advanced social behavior between students and instructors. For instance, students can approach their instructors with the problems that they had during the lectures, or work together with their peers to create research proposals for their classes (Ren et al., 2025; Staddon, 2023). Additionally, through gaining these technical skills in relation to the digital learning environment, students may have more positive perceptions regarding the interactions between students and instructors within digital environments. Students who feel that they are technically competent with the digital learning environment will have more positive perceptions of the interactions between students within digital environments (Ren et al., 2025; Zhao et al., 2025). Consequently, having technical competence can be a social enabler that instils confidence in students and gives them the operational flexibility to ask their instructors for help and share strategies with their classmates in their AI-supported research workflow (Luo et al., 2025; Staddon, 2023).

It has been demonstrated that social competencies significantly influence communication competence, further affirming the interactive nature of AI-supported research settings. In modern universities, students are increasingly expected to possess effective communication skills alongside prompt engineering skills, that is, the ability to formulate the right queries and requests in response to generative AI so as to elicit meaningful responses (Knoth et al., 2024; Federiakin et al., 2024). The evidence produced in this research study indicates that this competence is not developed in isolation but is expanded through social modelling and collaborative feedback processes (Jesus et al., 2024; Zapata et al., 2025).

Through their interactions with instructors, students are informed of the academic expectations regarding the ethical use of AI, scholarly standards, and rhetorical precision in research communication (Staddon, 2023; Zhu et al., 2025). Learning from classmates also disseminates technology practices. This includes exchanging successful prompt recipes and evaluating AI-generated summaries and research outputs (Jesus et al., 2024; Ke et al., 2025; Zapata et al., 2025). Through this social scaffolding, students can transition from providing simple commands to AI applications to the more complex communications required to effectively utilize these AI tools (Abdalla, 2024; Kim et al., 2025; Korchak et al., 2025).

Furthermore, the revelation of social competencies as a fully mediating variable is another of the study's main contributions to the existing literature. The finding that technical competence is not related to communication competence but is instead related to social competence contributes to the knowledge of the field of educational technology research in particular. Being technically skilled in operating digital systems does not necessarily mean having the communicative competence to interact effectively with AI (Kim et al., 2025; Federiakin et al., 2024). Even though students might have the technical know how to access AI systems themselves and generate an initial output, the capacity to iteratively communicate, critically engage with, and contextually enhance AI narratives reflects a more advanced level of scholarly competence that is often developed through social engagement and collaborative learning (Knoth et al., 2024).

Academics fear that AI essay-writing tools could be used to cheat. Socialising provides students with feedback mechanisms, as well as a diversity of perspectives that they can leverage to improve their communication practices and integrate generative AI's output into their reasoning (Obadă et al., 2026; Ren et al., 2025). Technical skills could remain procedural without the enabling functions of instructor guidance and peer collaboration. In addition, a technical skill such as 'building a search string' may require procedural knowledge and not lead to communicative competence necessary for effective AI-supported research (Kim et al., 2025; Wang & Gao, 2025).

The findings are consistent with the existing literature on online learning readiness and collaborative learning. In early research, the dimensions of the SOLR framework were often treated as parallel predictors of course satisfaction and academic engagement. By contrast, our study provides support for a more dynamic structural perspective where readiness competencies may function sequentially in a developmental manner. Moreover, these findings support technology adoption models, notably the unified theory of acceptance and use of technology, which emphasizes the significance of social influence in dictating behaviours towards technology (Alshammarı et al., 2025; Ke et al., 2025). However, the present analysis goes further by conceptualizing social competencies not just as external factors but as internal readiness mechanisms that enable students to develop the communicative competencies required to engage in human–AI interaction.

Implications

Theoretical Implications

The study also makes several theoretical contributions to the existing literature. For instance, it enhances the SOLR framework by revealing the structural associations of each competency with AI-assisted academic research. Previous studies have mostly considered each of the SOLR dimensions as precursors to learning results from online courses. However, the findings of this study demonstrate the sequential associations of these competencies: technical competence improves social competencies, which improve communication competence. Thus, this study improves the theoretical understanding of the SOLR dimensions as they relate to each of the technology learning environments.

Second, this study also makes a contribution to the existing theoretical discussion on AI-assisted learning and digital competence. One of the findings of this research is that having technical competence in the use of AI technologies does not necessarily indicate that an individual will have communication competence in the context of AI-assisted research. The growth of communication competence within these research contexts emerges from the social interactions that students have when collaborating with instructors and other students. The implications of this research highlight the need for theoretical models of student engagement with any new technology to include considerations of social learning. Furthermore, the findings of this research indicate that social competencies fully mediate the relationship between the independent variable of technical competence and the dependent variable of communication competence within the context of AI-assisted research.

Moreover, these results also provide better insights into the interaction between humans and AI in academic environments. As AI becomes more prevalent in academic assignments and dissertations, the concept of communication competence relates to the skills required to formulate questions and prompts for AI, to review the text that is generated by AI systems, and to incorporate those generated texts into academic work. The results of this study reveal that students acquire these skills through interacting with their peers and instructors and through trial and error in the classroom. The implications of these findings allow the SOLR framework to be extended to include the development of AI competence in educational environments.

Practical Implications

The findings are valuable for higher learning institutions, instructors, and course developers who wish to utilize

AI tools successfully in academic research practices. The first step universities need to take is to realize that developing students' competences in using AI tools does much more than just provide technical assistance. Although technical competence enables individuals to engage with AI systems, the findings indicate that social interaction and participatory learning processes mainly foster the development of communicative competence. Educational initiatives should forge a tripartite synergy that encompasses technical training as well as socialization and intellectual and cultural exchanges.

Additionally, the findings reveal that educators play an important role in effectively engaging learners with generative AI. Educators should instruct students in the proper authoring of prompts, critically analysing responses generated by generative AI, and ethically using AI-generated input in school tasks. When faculty members guide students to use AI responsibly, the students learn proper rhetorical and analytic strategies for using AI as a research partner rather than a mere content generator.

The third recommendation is that higher education institutions should create learning environments that promote the sharing of strategies for AI-related research among students. Peer interaction leads to the sharing of effective prompts, problem-solving of AI issues, and collective analysis of AI-generated results. Joint research projects, peer assessments, and AI-assisted discussion forums can strengthen students' communicative competence and allow for social-learning experiments with AI.

The findings highlight the challenge facing universities to develop a more holistic AI incorporation plan. Institutions should aim to create learning situations that simultaneously develop technical, social, and communication abilities, instead of focusing only on the functioning of the tools. This team approach will provide a much better way to prepare students to engage with AI technologies in ways that inspire critical inquiry, collaborative research, and responsible knowledge creation in today's universities.

Limitations and Future Research

This research study is not without limitations, which should be taken into consideration in future research. First of all, the study used a cross-sectional research design. In other words, it captured the perceptions of students at a particular time. Although SEM can be used to analyse complex relationships involving latent constructs, it does not allow for causal inferences. Applying longitudinal and experimental research to better evaluate the competencies and interactions of students over time will help to provide evidence regarding the causal relations between the different competencies.

Second, the fact that only a single university is used to collect the data limits the generalizability of the study. The characteristics and factors of individual universities may impact students' readiness to utilize these AI tools for their research tasks. Future research could utilize the model to collect data from students from a variety of universities, disciplines, and even countries to determine the generalizability of these findings.

Third, the study focused on competencies selected from the SOLR framework, specifically technical competence, social competence with instructors, social competence with classmates, and communication competence. While the SOLR model was developed to investigate students' readiness to use AI in their research work, there are other factors that could impact the way students use AI effectively. Future developments of the SOLR model could incorporate constructs such as AI literacy, critical AI awareness, collaborative learning, and self-regulated learning to investigate how these components influence students' effective use of AI in their research work.

Conclusion

The rapid adoption of artificial intelligence tools in higher education is changing the way students carry out their research. Based on these developments, this study investigated whether the competency that students have in interacting with others in the classroom mediates the effect of their technical competence with AI tools on their communication competence in the context of carrying out research. Using the framework of the Student Online Learning Readiness framework, the study found that students' technical competence has a positive impact on their social competencies with instructors and peers. Furthermore, these social competencies develop students' communication competence. While the direct effect of technical competence on communication competence was not found to be significant, the bootstrapping analyses did reveal that students' social competency with instructors and classmates significantly mediate the effect of their technical competence on their communication competence when carrying out research projects.

These findings indicate that being technically ready for AI tools does not ensure effective communication with these tools. It is not a matter of knowing how to use technology; however, effective communication and collaboration with AI tools in the academic research process require that students' technical knowledge develops into communication skills. The study sheds light on the social interaction that takes place in the classroom in the presence of AI tools and provides insight into the skills that students need to effectively conduct academic research with the aid of AI tools. Based on these findings, institutions of higher learning should implement a comprehensive approach to educating their students that focuses on developing the technical, social, and communication skills that will enhance their abilities to complete AI-assisted academic tasks.

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