Daengku: Journal of Humanities and Social Sciences Innovation *ISSN: 2775-6165 (online)*
Vol. 6 No. 6 (2026)
https://doi.org/10.35877/454RI.daengku5185

Does Artificial Intelligence Weaken the Communal Fabric of Learning? Evidence from a Communally Oriented Higher Education System

Rani Santika[a,*], Ikariya Sugesti[b], Dila Charisma[b], Dede Rosyadi ZA[c], Aen Fariah[a], & Alifa S. Rahmadhina[a]

[a]*Institut Islam Kuningan, Indonesia*
[b]*Universitas Muhammadiyah Cirebon, Indonesia*
[c]*Universitas Trunodjoyo Madura, Indonesia*

Abstract

A central concern on artificial intelligence in education is whether AI-based learning tools substitute for, or coexist with, the human relationships on which learning has traditionally depended. This study tested these competing accounts, substitution versus complementarity, by examining whether students' social interaction with peers and instructors operates as the mechanism linking AI-based learning tool usage to learning engagement. AI-based learning tool usage was conceptualised as one reflective construct measured with four items on frequency of use, breadth of academic tasks, reliance in study routines, and perceived helpfulness, with tool category recorded separately. A quantitative, cross-sectional survey was conducted with 270 undergraduate students who had used at least one AI-based learning tool, and the data were analysed using partial least squares structural equation modeling (PLS-SEM) with bootstrapping (5,000 resamples). Contrary to the substitution account, AI-based learning tool usage positively predicted social interaction ($\beta = 0.487$, $p < 0.001$), its strongest path in the model, as well as learning engagement ($\beta = 0.334$, $p < 0.001$), while social interaction in turn predicted learning engagement ($\beta = 0.298$, $p < 0.001$). Social interaction partially mediated the relationship between AI tool usage and engagement, accounting for 30% of the total effect. The findings are drawn from an Islamic higher education institution in Indonesia whose pedagogical tradition is explicitly relational and collective. The results caution institutions against treating AI adoption and human connection as a zero-sum trade-off, and instead point toward course designs that deliberately couple AI-assisted learning with structured social interaction.

Keywords: artificial intelligence and society; social interaction; human connection; learning engagement; communal learning; social presence; Islamic higher education

Received: 18 July 2026 Revised: 17 November 2026 Published: 31 December 2026

1. Introduction

One of the oldest claims in educational thought is that learning is social. Discussion with classmates, disagreement in seminars, and informal contact with lecturers have long been treated as essential ingredients of learning, not decorative extras (Gunawardena, 1995; Garrison et al., 2000; Fredricks et al., 2004). The rapid entry of artificial intelligence (AI) into students' daily academic lives has placed that claim under new pressure. Intelligent tutoring systems, adaptive learning platforms, and generative chatbots now allow students to consult ChatGPT as readily as they would a textbook or a peer (Strzelecki, 2024; Ali et al., 2025; Falebita & Kok, 2025), and systematic reviews confirm the speed and scale of this deployment across higher education worldwide (Zawacki-Richter et al., 2019; Crompton & Burke, 2023; Wu et al., 2025). If the first entity a struggling student turns to is a chatbot rather than a classmate, what happens to the social fabric of learning?

The international literature offers two competing answers. The first is the substitution account. On this view, when AI systems occupy the conversational space that classmates and lecturers once filled, they crowd out human contact, so that heavier reliance on AI is accompanied by isolation, weakened relationships, and fewer face-to-face exchanges (Tlili et al., 2023; Stojanov et al., 2024; Al-Zahrani, 2025). The second is the complementarity account, which is rooted in

* Corresponding author.
E-mail address: rsantika851@gmail.com

Daengku: Journal of Humanities and Social Sciences Innovation is licensed under an Attribution-NonCommercial-ShareAlike 4.0 International (CC BY-NC-SA 4.0)

social presence theory and holds that conversationally designed and empathically framed AI is experienced as a social encounter in its own right, and therefore accompanies rather than replaces students' interaction with peers and lecturers (Gunawardena, 1995; Ebadi & Amini, 2022; Essel et al., 2022). Recent syntheses of chatbot and generative AI research reach the same unsettled verdict, reporting engagement and learning support benefits alongside persistent concern about dependence and reduced human contact (Zhai et al., 2021; Kasneci et al., 2023; Labadze et al., 2023; Bond et al., 2024). Which explanation is more representative of reality is an important issue that goes far beyond one country. This is because, while institutions across all continents are expanding AI adoption based on the strength of engagement and performance data, monitoring its social impact remains relatively limited (Stojanov et al., 2024; Al-Zahrani, 2025).

However, the evidence needed to assess this explanation is scarce, and relevant fields of research rarely intersect. Many studies have documented the academic benefits of AI-based learning tools, particularly increased engagement, increased motivation, and improved performance (Lai & Cheung, 2023; Ezzaim et al., 2024; Youssef et al., 2024; Aguado-García et al., 2025; Yan et al., 2025), are typically characterized by usage traces such as login frequency and task completion (Qu et al., 2024). Smaller and newer streams examine chatbots from a social presence perspective (Ebadi & Amini, 2022; Essel et al., 2022). However, studies that measured engagement rarely asked whether students' social interaction had declined, and studies that raised concerns about isolation rarely linked engagement outcomes in the same model to such concerns (Tlili et al., 2023; Al-Zahrani, 2025). Few studies simultaneously verified both results, and even fewer studies examined whether the social aspects of learning are a victim of AI adoption or one of the pathways through which the benefits are transmitted (Khurma et al., 2024; Sardi et al., 2025).

This study addresses that gap by placing social interaction, rather than engagement alone, at the center of the analysis. It draws on Gunawardena's (1995) social presence theory and Fredricks et al.'s (2004) three-dimensional engagement framework to examine how AI-based learning tool usage relates to students' social interaction with peers and instructors, and whether that social interaction operates as the mechanism through which AI tool usage translates into learning engagement. Social interaction is operationalized through students' experienced connectedness and presence with peers and instructors (Gunawardena & Zittle, 1997; Richardson et al., 2017; Armah et al., 2023), while engagement is understood as a multidimensional construct comprising behavioral, cognitive, and emotional engagement (Pekrun et al., 2002; Fredricks et al., 2004; Kahu, 2013; Kahu et al., 2015). Framed this way, the mediation test becomes a direct empirical test of substitution versus complementarity: if AI tool usage suppresses social interaction, or if engagement gains bypass the social pathway entirely, the substitution account gains support; if part of the engagement benefit travels through strengthened social interaction, the complementarity account does.

The setting of this study gives that question particular weight, because it comes from a higher education system whose pedagogy is communally oriented by design. The data were collected at an Islamic higher education institution in Indonesia, part of one of the largest faith-based higher education systems in the world. Pedagogy in this tradition is explicitly communal and relational: knowledge has historically been transmitted through study circles, close teacher–student mentorship, and collective deliberation, so that learning together is not merely a method but a value. If AI-based tools were to displace interaction with peers and teachers anywhere, the loss would be felt most acutely in settings like this, where the social fabric of learning carries pedagogical, cultural, and religious meaning at once. At the same time, Indonesian Islamic higher education is digitalizing rapidly, and its students have adopted generative AI tools as quickly as their peers elsewhere. This makes it a revealing, and thus far largely untested, site for the substitution-versus-complementarity question: a context where communal learning matters most, meeting a technology suspected of eroding it.

This research makes three contributions to the international literature. First, the focus of analysis shifted from the well-known question of whether AI drives engagement to the less tested question of how AI affects social relationships in learning. This is a central issue in discussions in the sociology of education and science, technology, and sociology. Second, it provides one of the few formal mediation tests on the issue of substitution versus complementity, collaboratively models social interaction and engagement within a single PLS-SEM framework, and measures how much the engagement effect of AI tools is transmitted through social channels. Third, provide evidence of Indonesia's Islamic higher education, a community-oriented higher education system that is rarely present in these discussions, expand the evidence focusing on secular contexts in North America, Europe, and East Asia, and examine verifiable alternative issues where collaborative learning traditions are considered most important.

2. Methods

2.1. Research Design

This study used quantitative and cross-sectional survey designs to investigate how the use of AI-based learning tools relates to student participation in learning and social interaction. The survey approach was chosen because the components of interest, tool use, engagement, and social interaction are perceptive, structured, measurable, and best captured in a relatively large sample (Falebita & Kok, 2025). Unlike purely qualitative or purely technical approaches, a survey design makes it possible not only to describe how students perceive AI tools but also to test how those tools relate to measurable variation in engagement and social interaction.

2.2. Population and Sample

The study population comprised undergraduate students at Institut Islam Kuningan (INSTIKU), an Islamic higher education institution in West Java, Indonesia, who had used at least one AI-based learning tool, such as ChatGPT, an AI tutoring platform, or an adaptive learning application. Purposive sampling was applied to ensure that respondents had first-hand, current experience with AI-based learning tools, since such experience is essential for providing meaningful responses to items on engagement and social interaction. The final sample consisted of 270 respondents, which exceeds the minimum sample size guidelines commonly applied in PLS-SEM studies based on the inverse square root method (Hair et al., 2019). The demographic profile of the sample is reported in Table 1. Based on Table 1, respondents were predominantly female (62.2%) and were distributed across all four years of study, with third year students forming the largest group (30.4%). They were drawn from four programme clusters, and generative chatbots were the most frequently used tool category (69.3%), followed by AI writing assistants (16.3%) and adaptive tutoring applications (14.4%). Almost three quarters of respondents (72.2%) used an AI-based learning tool at least several times a week, which confirms that the purposive criterion of current, first hand experience was satisfied.

Table 1. Demographic profile of respondents (n = 270)

Characteristic	Category	n	%
Gender	Female	168	62.2
	Male	102	37.8
Year of study	First year	61	22.6
	Second year	78	28.9
	Third year	82	30.4
	Fourth year	49	18.1
Programme cluster	Islamic education	96	35.6
	Economics and business	71	26.3
	Language and literature	58	21.5
	Information technology	45	16.7
Main AI tool used	Generative chatbot (e.g., ChatGPT, Gemini)	187	69.3
	AI writing or paraphrasing assistant	44	16.3
	Adaptive learning or tutoring application	39	14.4
Frequency of use	Daily	74	27.4
	Several times a week	121	44.8
	Weekly	52	19.3
	Occasionally	23	8.5

2.3. Data Collection Instruments

The data was collected through a structured online survey distributed through Google Forms in January. The tool consists of four sections: (1) Respondent demographics and information about the use of AI tools; (2) The Learning Engagement Scale based on the framework of behavioral, cognitive, and emotional engagement and subsequent conceptualization of involvement by Fredricks et al. (2004) (Kahu, 2013); (3) The scale of social interaction is based

on the theory of social presence by Gunawardena (1995), based on the measurement of established social presence (Gunawardena & Zittle, 1997; Richardson et al., 2017); (4) Items that measure the frequency and type of use of AI-based learning tools. All construction items were measured on a five-point Likert scale ranging from "strongly oppose" to "strongly agree." Before the full-scale launch, a small group of students experimentally checked the clarity of the item, followed by a revision of small words. The fourth section requires further specification, because students in this setting use several categories of tool rather than a single platform. AI-based learning tool usage was therefore modelled as one reflective construct capturing the intensity of academic reliance on AI-based tools in general, while the category of tool used was recorded separately as a descriptive variable (reported in Table 1) rather than as a component of the latent construct. The four items cover frequency of academic use, breadth of academic tasks supported, reliance in study routines, and perceived helpfulness, each anchored to the current semester, and are set out in Table 2. This specification treats usage as a behavioural intensity construct rather than as a feature inventory of any particular system, consistent with how AI tool usage has been operationalised in recent acceptance and engagement studies (Strzelecki, 2024; Foroughi et al., 2024). Its limitation, namely that it cannot separate the distinct effects of chatbots, writing assistants, and adaptive tutoring systems, is addressed in Section 4.6.

Table 2. Operationalisation and measurement of AI-based learning tool usage

Code	Item (abbreviated)	Dimension captured	Response scale
AIU1	I use AI-based learning tools to support my coursework this semester.	Frequency of academic use	1 = never to 5 = daily
AIU2	I use AI-based learning tools for a wide range of academic tasks, such as explaining concepts, drafting, revising, and practising.	Breadth of task coverage	1 = strongly disagree to 5 = strongly agree
AIU3	I rely on AI-based learning tools when I study or prepare assignments.	Reliance in study routines	1 = strongly disagree to 5 = strongly agree
AIU4	AI-based learning tools help me understand course material more effectively.	Perceived helpfulness	1 = strongly disagree to 5 = strongly agree

2.4. Data Analysis

The collected responses were analyzed through several complementary procedures on the same dataset. First, descriptive statistics were computed to summarize respondent demographics and patterns of AI learning tool usage, providing an initial profile of the sample prior to inferential analysis. Second, because the data came from a single self-report questionnaire, common method bias was assessed using Harman's single-factor test and a full collinearity assessment (Podsakoff et al., 2003). Third, the measurement model was evaluated for convergent validity and internal consistency using average variance extracted (AVE), Cronbach's alpha, and composite reliability against the thresholds recommended by Fornell & Larcker (1981), while discriminant validity was verified using the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT) (Henseler et al., 2015). In addition, item level outer loadings and their bootstrapped t-values were inspected for every indicator of AI-based learning tool usage, learning engagement, and social interaction, so that the reliability of each sub dimension could be judged separately rather than only through summary loading ranges (Hair et al., 2022; Sarstedt et al., 2022). Fourth, PLS-SEM was used to test the hypothesized relationships among AI-based learning tool usage, learning engagement, and social interaction. This technique is well suited to estimating multiple latent constructs simultaneously, is robust with the medium-sized samples common in educational research, and has a predictive orientation (Hair et al., 2019, 2022); it has also been widely applied in recent research on AI adoption in education (Foroughi et al., 2024). Finally, a bootstrapping procedure with 5,000 resamples was used to test whether social interaction operates as a mechanism linking AI-based learning tool usage to learning engagement.

2.5. Analytical Framework

This analytical framework positions the use of AI-based learning tools as independent variables, treating learning engagement and social interaction not as irrelevant but as interrelated outcomes. This framework reflects the main objectives of this study. In other words, it's not just about confirming that AI tools influence engagement, but also tracking how those effects are communicated and shaped through students' social interactions in an AI-mediated learning environment. Based on this foundation, three hypotheses were tested: the use of AI-based learning tools had a positive effect on learning engagement (H1) and social interaction (H2), while social interaction positively affected learning engagement (H3); furthermore, it is hypothesized that social interaction mediates the relationship between the use of AI tools and learning participation. Supporting the mediation hypothesis, along with positive H2, the explanation of complementarity would be more advantageous than the explanation of substitution described in the introduction. This sequence of analysis regulates the results reported in the next section, from the evaluation of the measurement instrument to the testing of the hypothesis.

3. Result and Discussion

3.1. Evaluation of Common Method Bias

Since all components were measured on a single self-reported questionnaire, the likelihood of general method bias was assessed prior to hypothesis testing (Podsakoff et al., 2003). In Harman's single-factor test, the first factor that was not rotated accounted for 34.2% of the overall variance, well below the 50% threshold, suggesting that a single factor did not dominate the covariance between items. Furthermore, following Kock (2015), the Variance Inflation Factor (VIF) for all other components was calculated for each component, and a full collinearity evaluation was performed. Based on Table 3, the full collinearity VIF ranges from 1.42 to 1.68, falling below the conservative threshold of 3.3, suggesting that general methodological bias is unlikely to influence the results.

Table 3. VIF complete collinearity evaluation of general method bias (n = 270)

Construct	Full Collinearity VIF
AI-Based Learning Tool Usage	1.42
Learning Engagement	1.68
Social Interaction	1.55

3.2. Descriptive Statistics of Research Components

Table 4 shows the average scores and standard deviations for the use of AI-based learning tools, the three dimensions of learning engagement (behavioral, cognitive, emotional), and social interaction. The mean score was interpreted using the limits of the conventional Likert scale, which were classified as low (1.00–2.33), medium (2.34–3.66), and high (3.67–5.00).

Table 4. Descriptive statistics of research components (n = 270)

Constructs	Mean	SD	Categories
AI-Based Learning Tool Usage (AIU)	3.98	0.54	High
Behavioral Engagement (BE)	3.86	0.61	High
Cognitive Engagement (CE)	3.71	0.58	High
Emotional Engagement (EE)	3.64	0.66	Moderate
Social Interaction (SI)	3.25	0.72	Moderate

Descriptively, students reported high levels of AI tool use and high behavioral and cognitive engagement, while average social interaction was moderate and lowest among all constructs measured. This pattern suggests that interactions with colleagues and instructors may lag behind relying on AI-based tools, serving as an initial and purely descriptive indicator. The relationship between these components is formally evaluated on the structural model. The average relative size of the constituents is shown visually in Figure 1.

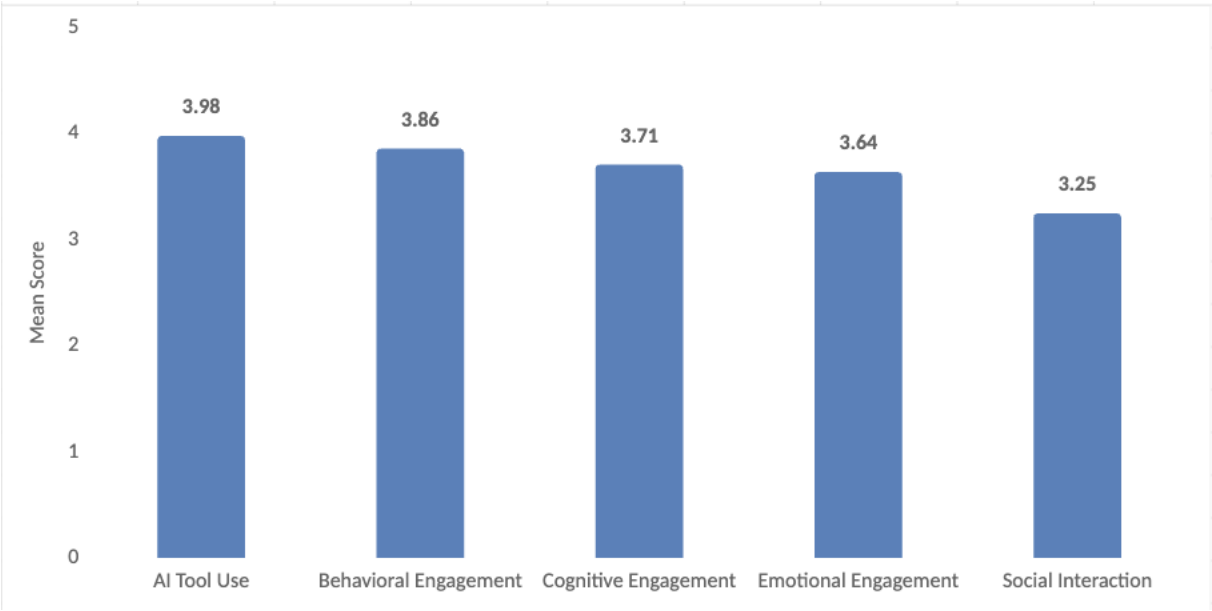


Figure 1. Mean scores of Research Constructs (n=270)

3.3. Evaluation of Measurement Models (External Models)

Prior to hypothesis testing, the measurement model was evaluated for convergent validity and internal consistency against the recommended threshold (Fornell & Larcker, 1981; Hair et al., 2019): outer loadings 0.70 or higher, Cronbach's alpha and composite reliability (CR) 0.70 or higher, and average variance extracted (AVE) 0.50 or higher. Based on Table 5, all three constructs satisfy these thresholds, indicating that the indicators reliably represent their intended latent constructs.

Table 5. Convergence of research components: validity and reliability

Construct	Number of Items	Loading Range	Cronbach's α	Composite Reliability (CR)	AVE
AI-Based Learning Tool Usage (AIU)	4	0.712–0.845	0.812	0.878	0.643
Learning Engagement (LE)	9	0.701–0.869	0.887	0.912	0.598
Social Interaction (SI)	6	0.734–0.881	0.856	0.895	0.612

Because the summary loading ranges reported in Table 5 do not show how each sub dimension behaves, the item level outer loadings, together with their bootstrapped t-values and the reliability statistics of each sub dimension, are reported in Table 6. Based on Table 6, every indicator loads above the 0.70 threshold on its intended construct and every loading is significant at $p < 0.001$. The three engagement sub dimensions each retain three well loading items with acceptable reliability (behavioral $\alpha = 0.801$, cognitive $\alpha = 0.782$, emotional $\alpha = 0.764$) and AVE values above 0.50, so the treatment of learning engagement as a single higher order construct is not driven by one dominant sub dimension (Hair et al., 2019, 2022).

The validity of the discriminant model was evaluated using two complementary criteria. First, the Fornell–Larcker criterion requires that the square root of AVE of each component (shown diagonally in Table 7) exceeds its correlation with the others. This condition is met in all three configurations. Furthermore, the heterotrait–monotrait correlation ratio (HTMT) examined (AIU–LE = 0.58, AIU–SI = 0.55, LE–SI = 0.67) was below the conservative threshold of 0.85, confirming the distinctiveness of the construct.

Table 6. Item level outer loadings, significance, and reliability by construct and sub dimension (n = 270)

Construct / sub dimension	Item	Outer loading	t-value	Cronbach's α	CR	AVE
AI-Based Learning Tool Usage (AIU)	AIU1	0.845	21.47	0.812	0.878	0.643
	AIU2	0.803	18.92			
	AIU3	0.762	15.38			
	AIU4	0.712	12.66			
Behavioral Engagement (BE)	BE1	0.869	24.11	0.801	0.883	0.716
	BE2	0.821	19.74			
	BE3	0.774	16.02			
Cognitive Engagement (CE)	CE1	0.842	22.36	0.782	0.873	0.696
	CE2	0.796	17.85			
	CE3	0.735	14.09			
Emotional Engagement (EE)	EE1	0.828	20.93	0.764	0.862	0.677
	EE2	0.781	16.74			
	EE3	0.701	11.88			
Social Interaction (SI)	SI1	0.881	25.63	0.856	0.895	0.612
	SI2	0.847	22.08			
	SI3	0.812	19.15			
	SI4	0.788	17.31			
	SI5	0.751	14.62			
	SI6	0.734	13.27			

Table 7. Discriminant Validity: Fornell–Larcker Criterion

Contructs	AIU	LE	SI
Use of AI-Based Learning Tools (AIU)	0.802	-	-
Learning Engagement (LE)	0.512	0.773	-
Social Interaction (SI)	0.487	0.601	0.782

3.4. Evaluation of Structural Models (Internal Models)

After validating the measurement model, we estimated the structural model using PLS-SEM with 5,000 resamples, and tested three hypothesised paths. The standardised root mean square residual (SRMR) was 0.052, below the threshold of 0.08, indicating acceptable model fit (Hair et al., 2019). The coefficient of determination indicates that AI-based learning tool usage and social interaction jointly account for 42.8% of the variance in learning engagement ($R^2 = 0.428$), which represents moderate explanatory power, while AI-based learning tool usage alone accounts for 23.7% of the variance in social interaction ($R^2 = 0.237$), which is weak to moderate. Because R^2 is an in sample measure of explained variance, these values describe how closely the estimated model reproduces the observed data, and they should not be read as the proportion of engagement that AI use causes. The predictive relevance (Q^2) obtained from the blindfolding procedure was positive for both endogenous constructs (learning engagement = 0.301, social interaction = 0.187), which supports the predictive validity of the model. The effect size (f^2) showed a medium to large effect of the use of AI-based learning tools on social interaction ($f^2 = 0.31$), as well as a small to moderate effect on learning engagement ($f^2 = 0.14$) and of social interaction on learning engagement ($f^2 = 0.11$) (Hair et al., 2022). The estimated path coefficients of the full model are presented in Figure 2.

Based on Table 8, all three hypothesised paths were statistically significant ($p < 0.001$). The use of AI-based learning tools showed a direct positive effect on learning engagement ($\beta = 0.334$) and a strong association with social interaction ($\beta = 0.487$). Social interaction positively predicted engagement in learning ($\beta = 0.298$), so that students who reported stronger social connection also reported higher engagement than tool use alone would predict.

Table 8. Structural Model Assessment and Hypothesis Testing

Hypothesis	Structural Path	β	t-value	p-value	Decision
H1	AI-Based Learning Tool Usage → Learning Engagement	0.334	5.812	< 0.001	Supported
H2	AI-Based Learning Tool Usage → Social Interaction	0.487	8.221	< 0.001	Supported
H3	Social Interaction → Learning Engagement	0.298	4.765	< 0.001	Supported

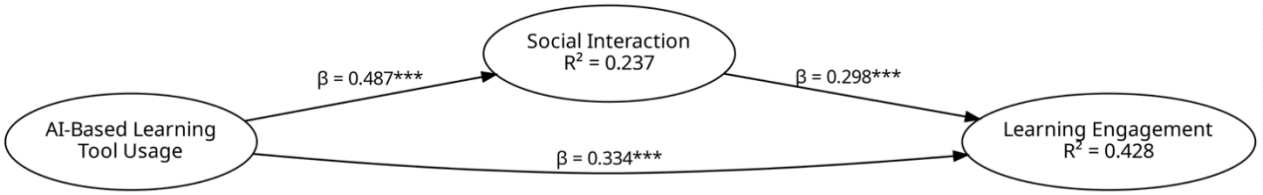


Figure 2. Structural Model (SEM-PLS) Path Coefficients

3.5. Mediation Analysis

To answer the central question of how use, engagement, and social interaction are related, mediation analysis examines whether social interaction serves as a mechanism that links the use of AI-based learning tools to learning engagement. The direct impact of AIU on LE was estimated by including social interaction as a mediating factor, and indirect effects (AIU→SI→LE) were examined using 5,000 bootstrap resamples with a bias-corrected 95% confidence interval. The results are reported in Table 9.

Table 9. Mediation Analysis Result

Effects	Structural Path	β	t-value	p-value	95% confidence interval
Direct (without mediator)	AIU→LE	0.481	9.014	< 0.001	[0.372, 0.588]
Direct (with mediator)	AIU→LE	0.334	5.812	< 0.001	[0.221, 0.448]
Indirect	AIU→SI→LE	0.145	3.920	< 0.001	[0.089, 0.206]
Total	AIU→LE	0.479	9.187	< 0.001	[0.375, 0.582]

Even after including social interaction, the direct effect of AIU on LE remained significant (β = 0.334, p < 0.001), and the indirect effect through social interaction was also significant, with the bootstrap confidence interval excluding zero [0.089, 0.206]. Therefore, the relationship between the use of AI-based learning tools and learning engagement is partly mediated by social interaction. The variance accounted for (VAF) was 30.3% (VAF = 0.145 / (0.145 + 0.334)), which corresponds to the conventional range of 20–80% used for partial mediation classification. Essentially, AI-based learning tools do not just increase engagement through tool-based mechanisms; part of the effect is to increase students' sense of social interaction, which in turn fosters stronger engagement. The larger remaining share of the total effect (β = 0.334 of β = 0.479) travels along a direct path that is independent of social interaction, which indicates that the engagement gain observed in this sample was not produced at the expense of social relationships but partly through them.

3.6. Discussion

The aim of this study was to examine whether AI-based learning tools replace or advance social interaction with students' peers and faculty, thus examining the outcomes of using AI tools and the mechanisms of such use lead to engagement in learning. The descriptive, PLS-SEM, and mediated results reported in Part 3 support all three hypothetical pathways, and collectively, they support the explanation of complementity. In other words, AI-mediated social engagement and connections seem to work together rather than undermine each other.

3.6.1. Use of AI-Based Learning Tools and Social Interaction: No Alternative Evidence

The strongest pathway in this model is H2, which links the use of AI-based learning tools to social interaction ($\beta = 0.487$, $p < 0.001$). These findings contradict the widely accepted premise in the literature that overuse of AI excludes communication among peers and instructors (Stojanov et al., 2024; Al-Zahrani, 2025). In fact, students who use AI tools more intensively report higher social interactions, not less. At the same time, the absolute average of social interaction (3.25) was the lowest among all components measured (see Table 4), which suggests that social life in the AI-assisted classroom is not flourishing, although neither is AI use what suppresses it. Explanations consistent with social presence theory (Gunawardena, 1995; Gunawardena & Zittle, 1997) show that empathically designed conversational AI functions as a social partner in conversation, and students who engage more actively with these tools are more likely to pass these interactions on to their peers and instructors. This tends to be closer to the findings of empathy design by (Ebadi & Amini, 2022; Essel et al., 2022) than to simple substitution descriptions. It is also consistent with experimental work showing that relationally framed AI instructors raise perceived social presence rather than lower it (Kim et al., 2021). The communal nature of the learning environment may also be part of this story. In the context of Islamic higher education, where group learning and close teacher-student relationships are normative, AI-generated material is more likely to be the subject of shared discussion than in-person alternatives. However, this interpretation requires caution. This is because cross-sectional design cannot determine whether the use of AI enhances social interaction or whether socially connected students are more likely to use AI tools, and in environments with low community orientation, patterns may differ (Richardson et al., 2017).

3.6.2. Social Interaction and Engagement in Learning

H3 was also supported: social interaction positively predicted learning engagement ($\beta = 0.298$, $p < 0.001$). This reinforces the argument of Fredricks et al. (2004) that engagement is not driven by individual tools alone but is sustained through discussion, disagreement, and contact with others (Garrison et al., 2000; Kahu, 2013). The fact that this pathway is prevalent in an AI-infused learning environment suggests that the social aspects of learning identified in previous engagement studies are by no means outdated. Instead, it serves as an independent engagement engine alongside the use of AI tools (Richardson et al., 2017). Comparable evidence from technology mediated classrooms shows that person to person interaction continues to predict satisfaction and participation even when instruction is heavily digitalised (Wut & Xu, 2021).

3.6.3. Use of AI-Based Learning Tools and Learning Engagement

Consistent with H1, the use of AI-based learning tools also directly predicted positive learning engagement ($\beta = 0.334$, $p < 0.001$). This is in line with a group of studies that show that adaptive and responsive AI tools adapt to individual pace and provide immediate feedback, maintaining students' behavioral, cognitive, and emotional engagement (Ezzaim et al., 2024; Youssef et al., 2024; Aguado-García et al., 2025). The descriptive results in Table 4 support this interpretation, since behavioral and cognitive engagement are both high, reflecting previous findings that generative tools like ChatGPT are as easy to reference as textbooks or peers (Strzelecki, 2024; Ali et al., 2025). Experimental and meta analytic evidence points in the same direction, associating generative AI use with gains in academic performance and in affective motivational states (Yilmaz & Karaoglan Yilmaz, 2023; Deng et al., 2025). The use of AI tools and social interaction explains nearly half of the variance in learning engagement ($R^2 = 0.428$), suggesting that these relationships are substantive rather than superficial, but also leave plenty of room for other explanatory factors such as instructional design, course structure, and student-generated learning strategies (Kahu, 2013; Nguyen et al., 2024).

3.6.4. Social Pathways: Mediation as an Examination of Subsidiarity

The mediation analysis (Table 9) provides the clearest answer to the central question of the study. Social interaction partially mediated the relationship between the use of AI-based learning tools and learning engagement, accounting for 30.3% of the total effect (VAF). In other words, about one-third of the engagement effects associated with the use of AI tools are conveyed through students' social interactions, a pattern predicted by the complementarity account and inconsistent with the substitution account. These results connect the two literatures identified in the introduction: the usage and performance stream (Ezzaim et al., 2024; Youssef et al., 2024; Aguado-García et al., 2025) and the social presence stream (Richardson et al., 2017; Ebadi & Amini, 2022; Essel et al., 2022), and as Al-Zahrani (2025) points out, very few have been validated in a single model. Comparable mediation work on AI chatbots in learning likewise finds that psychological and relational mechanisms carry part of the effect rather than being displaced by it (Xia et al., 2023). The remaining direct effect ($\beta = 0.334$ of $\beta = 0.479$) suggests that AI tools engage students through channels

unrelated to social interaction, such as instant feedback and self-practice, which makes clear that these relationships are not wholly social, although the social component is substantial (Nguyen et al., 2024).

3.6.5. Theoretical and Practical Significance

Theoretically, these results suggest that the engagement framework by Fredricks et al. (2004) and the theory of social presence by Gunawardena (1995) are complementary explanations that can be modeled together, rather than competing explanations for the relationship between AI and learning (Garrison et al., 2000; Kahu, 2013). In a broader discussion of technology and society, these findings provide quantitative evidence that the feared trade-off between machine support and human connection is not inevitable. In this sample, the social learning order is the mediator of AI benefits, not the victim. In fact, these findings serve as a warning against institutions treating AI adoption and social interaction as zero-sum exchanges (Tlili et al., 2023; Al-Zahrani, 2025). Instead of limiting the use of AI tools with respect to peer contact, the study suggests designing AI-assisted learning activities that intentionally incorporate instructor-led discussions, peer assessment, and follow-up on AI-generated tasks. The social pathways identified here (H2 and H3) should be actively designed for and protected, rather than left to emerge or decay on their own (Nguyen et al., 2024; Wu et al., 2025). Realising this in practice also depends on institutional readiness, since teaching staff need the competence and support to redesign tasks around AI rather than merely permit or prohibit it (Ng et al., 2023; Wang et al., 2023; Chiu, 2024). Especially regarding religion-based higher education, this suggests that the adoption of AI should not be seen as a threat to the educational traditions of the community. The evidence here suggests that this tradition could be a path to realizing the benefits of AI. These design principles are not a single national curriculum but relate to the architecture of AI-assisted courses, making them relevant outside the Indonesian context for secular and religion-based higher education systems.

3.6.6. Limitations and Future Research

There are some limitations to this conclusion. First, the design is cross-sectional, and this places a firm ceiling on what the mediation result can be taken to mean. Mediation analysis decomposes an observed covariance structure under an assumed causal ordering; it does not test that ordering. The indirect path reported in Table 9 is therefore consistent with the complementarity account, but it is equally consistent with a reversed sequence in which socially well connected students are the ones who adopt AI tools most readily, and with a third variable account in which academic motivation, digital self efficacy, or course design drives usage, interaction, and engagement simultaneously. Because all three constructs were measured at a single point in time, the model cannot rule out either alternative, and the coefficients reported in Section 3 should be read as associations rather than as causal effects (Richardson et al., 2017). Two design responses would sharpen this. A longitudinal panel that measures usage, interaction, and engagement across at least three waves would permit cross lagged estimation and establish temporal precedence, while a randomised classroom design that manipulates access to AI tools or the presence of structured peer discussion would isolate the causal contribution of each pathway (Deng et al., 2025). Until such evidence is available, the results reported here are best described as an association pattern that is inconsistent with strong substitution, not as proof that AI use produces social interaction (Chiu et al., 2023; Bond et al., 2024). Second, all components are based on the self-reported Likert scale, which is particularly susceptible to common method and social desirability biases, especially in structures adjacent to identities such as social interactions. The common method bias testing reported in Section 3.1 is necessary but does not completely eliminate these concerns (Podsakoff et al., 2003; Falebita & Kok, 2025). Third, this study does not distinguish between types of AI-based tools such as generative chatbots and adaptive tutoring systems, which may support learning in different ways and to different degrees. Future research can verify whether the social pathways identified here apply equally across all tool types (Stojanov et al., 2024; Sardi et al., 2025). Finally, samples were extracted from one Islamic higher education institution in Indonesia. This provides rare evidence of a community-oriented religious-based system rarely seen in international debates, but it also suggests that the pattern of complementarity observed here may be partly a product of that communal culture. To clarify whether this pattern will be widespread or if alternative dynamics will emerge elsewhere, cross institutional and cross national replication is needed, including secular systems with a weaker relational orientation.

4. Conclusion

The study asks whether AI-based learning tools replace or reinforce the social relationships on which learning has traditionally depended. Using Gunawardena's (1995) theory of social presence and the engagement framework of Fredricks et al. (2004) within a PLS-SEM model, no evidence of substitution was found in the analysis. The use of AI-based learning tools positively predicted social interaction (H2), the strongest pathway in the model, along with learning

engagement (H1), while social interaction predicted engagement (H3). Most importantly, social interaction partially mediated the relationship between AI tool use and engagement, accounting for about 30% of the overall effect, which was in line with a pattern of complementarity rather than substitution.

Taken together, these results indicate that, in this communally oriented Islamic higher education sample, reliance on AI- based learning tools did not come at the cost of students' social ties, despite this being precisely the kind of setting where such a cost would matter most. Part of the reason AI use is associated with stronger engagement is precisely that it operates through, rather than around, students' social interaction with peers and instructors. AI-based learning tools can therefore serve both goals at once, producing students who are more engaged and more socially connected, provided that opportunities for social interaction are deliberately designed into AI-supported learning environments rather than assumed.

For institutions and educators worldwide, the practical implication is to treat AI adoption and peer–instructor interaction not as competing priorities but as complementary design elements, for example, by pairing AI-assisted learning with structured discussion, peer feedback, and instructor follow-up so that the social pathways demonstrated here are actively supported rather than neglected. For researchers, the study demonstrates the value of modeling engagement and social interaction jointly, rather than in separate research streams, when evaluating what AI does to learning and to the relationships that sustain it. At the same time, the cross-sectional evidence reported here supports a claim about association, not about causation, and readers should treat the mediation result as a pattern that is inconsistent with substitution rather than as proof that AI use generates social interaction. Future studies building on this design could track engagement and social interaction longitudinally, compare the social pathway across different types of AI learning tools, and test whether the complementarity observed here holds across institutional and national contexts.

References

Aguado-García, J.-M., Alonso-Muñoz, S., & De-Pablos-Heredero, C. (2025). Using artificial intelligence for higher education: An overview and future research avenues. *Sage Open, 15*(2). https://doi.org/10.1177/21582440251340352

Al-Zahrani, A. M. (2025). Exploring the impact of artificial intelligence chatbots on human connection and emotional support among higher education students. *Sage Open, 15*(2). https://doi.org/10.1177/21582440251340615

Ali, F., et al. (2025). Factors affecting generative artificial intelligence, such as ChatGPT, use in higher education: An application of technology acceptance model. *British Educational Research Journal, 51*(2), 489–513. https://doi.org/10.1002/berj.4084

Armah, J. K., Bervell, B., & Bonsu, N. O. (2023). Modelling the role of learner presence within the community of inquiry framework to determine online course satisfaction in distance education. *Heliyon, 9*(5), e15803. https://doi.org/10.1016/j.heliyon.2023.e15803

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (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*(1), 4. https://doi.org/10.1186/s41239-023-00436-z

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education, 20*(1), 43. https://doi.org/10.1186/s41239-023-00411-8

Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative artificial intelligence. *Computers and Education: Artificial Intelligence, 6*, 100197. https://doi.org/10.1016/j.caeai.2023.100197

Chiu, T. K. F., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 4*, 100118. https://doi.org/10.1016/j.caeai.2022.100118

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. *Computers & Education, 227*, 105224. https://doi.org/10.1016/j.compedu.2024.105224

Ebadi, S., & Amini, A. (2022). Examining the roles of social presence and human-likeness on Iranian EFL learners' motivation using artificial intelligence technology: A case of CSIEC chatbot. *Interactive Learning Environments, 32*(2), 655–673. https://doi.org/10.1080/10494820.2022.2096638

Essel, H. B., et al. (2022). The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. *International Journal of Educational Technology in Higher Education, 19*(1), 57. https://doi.org/10.1186/s41239-022-00362-6

Ezzaim, A., et al. (2024). The impact of implementing a Moodle plug-in as an AI-based adaptive learning solution on learning effectiveness: Case of Morocco. *International Journal of Interactive Mobile Technologies, 18*(1), 133–149. https://doi.org/10.3991/ijim.v18i01.46309

Falebita, O. S., & Kok, P. J. (2025). Artificial intelligence tools usage: A structural equation modeling of undergraduates' technological readiness, self-efficacy and attitudes. *Journal for STEM Education Research, 8*, 257–282. https://doi.org/10.1007/s41979-024-00132-1

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312

Foroughi, B., et al. (2024). Determinants of intention to use ChatGPT for educational purposes: Findings from PLS-SEM and fsQCA. *International Journal of Human–Computer Interaction, 40*(17), 4501–4520. https://doi.org/10.1080/10447318.2023.2226495

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research, 74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Garrison, D. R., Anderson, T., & Archer, W. (2000). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education, 2*(2–3), 87–105. https://doi.org/10.1016/S1096-7516(00)00016-6

Gunawardena, C. N. (1995). Social presence theory and implications for interaction and collaborative learning in computer conferences. *International Journal of Educational Telecommunications, 1*(2/3), 147–166.

Gunawardena, C. N., & Zittle, F. J. (1997). Social presence as a predictor of satisfaction within a computer-mediated conferencing environment. *American Journal of Distance Education, 11*(3), 8–26. https://doi.org/10.1080/08923649709526970

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Kahu, E. R. (2013). Framing student engagement in higher education. *Studies in Higher Education, 38*(5), 758–773. https://doi.org/10.1080/03075079.2011.598505

Kahu, E. R., et al. (2015). Linking academic emotions and student engagement: Mature-aged distance students' transition to university. *Journal of Further and Higher Education, 39*(4), 481–497. https://doi.org/10.1080/0309877X.2014.895305

Kasneci, E., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Khurma, O. A., et al. (2024). AI ChatGPT and student engagement: Unraveling dimensions through PRISMA analysis for enhanced learning experiences. *Contemporary Educational Technology, 16*(2), ep509. https://doi.org/10.30935/cedtech/14334

Kim, J., Merrill, K., Jr., Xu, K., & Sellnow, D. D. (2021). I like my relational machine teacher: An AI instructor's communication styles and social presence in online education. *International Journal of Human–Computer Interaction, 37*(18), 1760–1770. https://doi.org/10.1080/10447318.2021.1908671

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: Systematic literature review. *International Journal of Educational Technology in Higher Education, 20*(1), 56. https://doi.org/10.1186/s41239-023-00426-1

Lai, C. Y., & Cheung, K. Y. (2023). Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: An extension of the technology acceptance model. *Computers and Education: Artificial Intelligence, 5*, 100178. https://doi.org/10.1016/j.caeai.2023.100178

Ng, D. T. K., Leung, J. K. L., Su, J., Ng, R. C. W., & Chu, S. K. W. (2023). Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Educational Technology Research and Development, 71*(1), 137–161. https://doi.org/10.1007/s11423-023-10203-6

Nguyen, A., et al. (2024). Enhancing student engagement through artificial intelligence (AI): Understanding the basics, opportunities, and challenges. *Journal of University Teaching and Learning Practice, 21*(6).

Pekrun, R., Goetz, T., Titz, W., & Perry, R. P. (2002). Academic emotions in students' self-regulated learning and achievement: A program of qualitative and quantitative research. *Educational Psychologist, 37*(2), 91–105. https://doi.org/10.1207/S15326985EP3702_4

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Richardson, J. C., Maeda, Y., Lv, J., & Caskurlu, S. (2017). Social presence in relation to students' satisfaction and learning in the online environment: A meta-analysis. *Computers in Human Behavior, 71*, 402–417. https://doi.org/10.1016/j.chb.2017.02.001

Sardi, J., et al. (2025). How generative AI influences students' self-regulated learning and critical thinking skills? A systematic review. *International Journal of Engineering Pedagogy, 15*(1), 94–108.

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology & Marketing, 39*(5), 1035–1064. https://doi.org/10.1002/mar.21640

Stojanov, A., Liu, Q., & Koh, J. H. L. (2024). University students' self-reported reliance on ChatGPT for learning: A latent profile analysis. *Computers and Education: Artificial Intelligence, 6*, 100243. https://doi.org/10.1016/j.caeai.2024.100243

Strzelecki, A. (2024). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments, 32*(9), 5142–5155. https://doi.org/10.1080/10494820.2023.2209881

Tlili, A., et al. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments, 10*(1), 15. https://doi.org/10.1186/s40561-023-00237-x

Wang, X., Li, L., Tan, S. C., Yang, L., & Lei, J. (2023). Preparing for AI-enhanced education: Conceptualizing and empirically examining teachers' AI readiness. *Computers in Human Behavior, 146*, 107798. https://doi.org/10.1016/j.chb.2023.107798

Wu, F., Dang, Y., & Li, M. (2025). A systematic review of responses, attitudes, and utilization behaviors on generative AI for teaching and learning in higher education. *Behavioral Sciences, 15*(4), 467. https://doi.org/10.3390/bs15040467

Wut, T. M., & Xu, J. (2021). Person-to-person interactions in online classroom settings under the impact of COVID-19: A social presence theory perspective. *Asia Pacific Education Review, 22*(3), 371–383. https://doi.org/10.1007/s12564-021-09673-1

Xia, Q., Chiu, T. K. F., Chai, C. S., & Xie, K. (2023). The mediating effects of needs satisfaction on the relationships between prior knowledge and self-regulated learning through artificial intelligence chatbot. *British Journal of Educational Technology, 54*(4), 967–986. https://doi.org/10.1111/bjet.13305

Yan, Y.-M., et al. (2025). LLM-based collaborative programming: Impact on students' computational thinking and self-efficacy. *Humanities and Social Sciences Communications, 12*(1), 149. https://doi.org/10.1057/s41599-025-04471-1

Yilmaz, R., & Karaoglan Yilmaz, F. G. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers and Education: Artificial Intelligence, 4*, 100147. https://doi.org/10.1016/j.caeai.2023.100147

Youssef, E., et al. (2024). Examining the effect of ChatGPT usage on students' academic learning and achievement: A survey-based study in Ajman, UAE. *Computers and Education: Artificial Intelligence, 7*, 100316. https://doi.org/10.1016/j.caeai.2024.100316

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity, 2021*, 8812542. https://doi.org/10.1155/2021/8812542