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AI Literacy, Epistemic Justification, and Synthetic Knowledge Evaluation among University Students: A Structural Equation Modelling Approach

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Abstract

Purpose: AI is increasingly incorporated into higher education, so knowledge of AI systems and critical enquiry of AI-generated knowledge is essential for students. The study explores the relationships between Epistemic Justification, Critical Thinking Disposition, AI Literacy, and Synthetic Knowledge Evaluation among university students. Specifically, it explores the relationships between AI Literacy and Epistemic Justification, the role of Epistemic Justification as a mediator, and Critical Thinking Disposition as a moderator.

Methodology: A survey technique of quantitative study is employed; the survey is conducted among 350 university students of New Delhi based on stratified random sampling; the survey instrument is a close ended questionnaire developed by the researcher. For demographic, SPSS is used and, for the Structural Equation Modelling analysis, SmartPLS 4 is used.

Findings: The results indicate that AI Literacy and Epistemic Justification predict the Synthetic Knowledge Evaluation and that the interaction between Critical Thinking Disposition yields a modest contribution. The study highlights the need for integrated AI literacy and evidence-based evaluation practices.

Unique Contribution to Theory, Practice and Policy: The study contributes to understanding responsible AI engagement by linking technological competence with evidence-based reasoning and critical knowledge evaluation. There are limitations to the cross-sectional design and contextual sample. Future studies could rely on longitudinal and mixed methods approaches.

Keywords: *AI Literacy; Epistemic Justification; Synthetic Knowledge Evaluation; Critical Thinking Disposition; Structural Equation Modelling.*

1. Introduction

Artificial Intelligence (AI) has become a salient feature of Higher Education (HE), changing how University students' access, process, create and evaluate information. Artificial Intelligence (AI) plays an increasingly important role in the University students' personal experience in Higher Education (HE), in their ways to: access, process, create and evaluate information. Generative AI, intelligent tutors and coaches, conversational agents, and AI-driven learning applications provide access to explanations, facts, ideas, and support in real time, giving students instant access to explanations, facts, ideas, and learning support [1]. It promises to bring improved flexibility, personalisation, and efficiency in the learning process, but it also poses new risks relating to information reliability and quality, generated by AI. Students are not only expected to rely on AI tools but to also comprehend how it functions, the merits and demerits of their working and how to evaluate their output. As a result, the use of AI in education is not just about technology; it's about cultivating students' mental skills to engage with and assess AI-generated content effectively and responsibly [2].

Analyzing the dynamic educational environment, AI literacy has emerged as a critical competency for university students. AI literacy includes recognizing and understanding core AI concepts, understanding how AI technologies create information, awareness of the capabilities and limitations of AI, and competent, responsible use of AI technologies. But being able to use an AI system does not imply that students can also gauge the accuracy or trustworthiness of its output [3]. Responses provided by AI might seem logical, knowledgeable, and persuasive, yet may also be incorrect, incomplete, referenced with made-up content, or have a slanted point of view. So, students must be able to not only use AI tools to perform a function but also raise queries about how the information produced is derived and how trustworthy it may be. This ensures that epistemic justification becomes a crucial aspect of AI-based learning, requiring students to assess whether the specific claim generated by the AI is backed by solid evidence and trustworthy sources [4].

Epistemic Justification is the ways by which people come to believe have enough reasons to believe that information or claims is good and should be accepted as true. This applies in university education to analysing an argument, assessing the credibility of sources, comparing the information provided in reliable sources, identifying any inconsistencies in an argument, and determining if the argument is logically supported. When paired with generative AI, these practices are even more critical, as AI-generated content can often sound convincing and authoritative without being accurate [5]. Pupils should for instance be able to recognise and differentiate information which at first glance may seem sensible to information that can be substantiated with suitable evidence. The power to challenge AI-generated statements, fact check key data, expand its boundaries of validity, and look for alternative sources of information can impact student learning from AI. Thus, epistemic justification provides an important link between students' understanding of AI and their ability to make informed judgments about AI-generated content [6].

The increased voluminosity of synthetic knowledge justifies the skills of evaluation. AI tools are now drawing knowledge, elaborations, deductions, arguments, and explanations from a vast body of information to re-combine and deliver it in different forms. Yet, while synthetic knowledge is beneficial to learning and effectiveness in school-centric tasks, concerns exist as to the accuracy, completeness, relevance, bias, contextual appropriateness, and evidence bases of synthetic knowledge used [7]. Synthetic knowledge evaluation thus means that students can compare the information provided by AI tools, as well as to judge if it is accurate, reliable, relevant, well-supported and suitable for academic contexts. By contrast, despite a growing body of study into the intersections of AI, generative AI and education, less attention is paid to the concerted relationship between epistemic justification, students' AI literacy, and their capacity to assess synthetic knowledge. Often, the more often a particular type of AI is used, the more likely it is to be considered responsible or critical; however, there are exceptions to the rule [8].

Accordingly, the present study examines AI Literacy, Epistemic Justification, and Synthetic Knowledge Evaluation among University Students through a Structural Equation Modelling (SEM) approach. The study acknowledges the significance of AI literacy for informed interaction with AI, epistemic justification as a critical process that students use to evaluate whether AI-produced information is credible and has convincing evidence, and synthetic knowledge evaluation as the ability to evaluate the quality and academic appropriateness of the AI's knowledge [9]. By analyzing these constructs in an overall structural view, a fuller picture of students' readiness for higher education integrated with AI emerges. The study also aligns with the ongoing debate surrounding responsible use of AI, not only because of the students' adeptness at leveraging AI technologies to produce knowledge but also through their questioning, verifying, and critical assessment of such knowledge produced from an AI system [10].

This study's value rests in its holistic approach to analysing AI literacy, epistemic justification, and synthetic knowledge assessment among university students—a three-way nexus that is becoming instrumental in AI-driven higher education. Students are quickly incorporating generative AI as part of their learning, but it must also have the knowledge and skills to assess, question, and consider the credibility, extent, and relevance of AI-generated facts and data, as well as the evidence, and its academic appropriateness. The study explores these constructs considering the empirical Structural Equation Modelling (SEM), thus giving empirical insight into the interconnections of these constructs. Results can be used to inform the design of AI literacy programs for universities and educators, focusing on critical awareness in verifying information, evidence-based thinking, and responsible knowledge evaluation. The study also aligns with the ongoing academic debate surrounding students' cognitive and epistemic preparedness in responsible use of AI tools.

The study starts with Introduction, which introduces background information, the need for study on AI Literacy, Epistemic Justification, and Synthetic Knowledge Evaluation, and the purpose of its examination. The Literature Review covers the topics of AI Literacy, Epistemic Justification, the Evaluation of synthetic knowledge, the Theoretical Foundation, and

Rationale. The Methods section describes the participants, data collection methods, instruments, and analysis. Results give demographic and SEM results followed by Discussion, the Conclusion, implications, limitations and suggestions for future study.

2. Literature Review

2.1. AI Literacy among University Students

AI literacy is becoming a vital skill in the modern educational landscape, and it encompasses more than just understanding technologies like AI; it includes knowledge, practical abilities and skills, critical thinking, and ethical considerations for engaging with AI systems [11]. Current conceptualisations suggest that AI literacy is not only about using AI tools or applications, but also about having knowledge of basic concepts of AI, applying AI tools and tools in context, analysing the outputs and implications of AI, and being aware of associated ethical concerns. For example, [12] identify four aspects of AI literacy: knowledge and understanding of AI, using AI, assessing AI use, and ethics of AI [13]. For university students, this multi-dimensional view is especially important since their engagement with AI is becoming an experience across the spectrum of information searching, academic writing, problem solving, content creation, and knowledge acquisition. Likewise, [14] highlights the value of human-centred thinking, ethical AI awareness, AI foundations and applications, AI pedagogy, and AI-supported professional development as some of the key areas for responsible AI engagement. It suggests that an understanding of AI literacy should be multi-faceted and consist of two elements; technical and critical, and that it should not be equated with technical skills [15].

The cognitive aspects of AI literacy are particularly relevant in the presence of AI-generated information. The knowledge and understanding of AI allow people to see how AI systems operate, what it can achieve, and where it fall short, whilst being able to apply AI involves the ability to use AI technologies in the appropriate way in various contexts [16]. The higher-order competencies, however, are particularly important since it involve assessing the quality, meaning, limitations, and potential biases of AI output. However, [12] and others have also found that the current literature on AI-literacy has often focused on cognitive skills at the lower levels of the cognitive taxonomy, such as understanding and using of AI concepts and perceptions, showing a relative lack in discussion of higher-order cognitive skills like critically evaluating and assessing with AI [15]. This separation is increasingly relevant in university education where it is essential that the learner can read information independently; evaluate conflicting information; design knowledge according to evidence-based reasoning. Therefore, AI literacy can offer students a conceptual underpinning for understanding that generated responses need to be fact-checked, not automatically accepted. Hence, AI literacy can help build students' conceptual understanding of the need for checking AI-generated responses [17].

Recent studies also provide another example of Fuzzy AI literacy domains in educational segments. According to [13] who studied 782 English teachers at 54 colleges and universities in 17 provinces in China, there are four AI literacy types, which are poor, fair, good, and excellent. Their results suggest that the overall levels of AI knowledge, AI use, and

AI ethics are more developed, while AI assessment and AI design are comparatively less developed across profiles. This is a valuable sign that being familiar with AI technologies doesn't align with high-level assessment skills, even though the study applies to teachers and not university students themselves. [17] defines AI literacy in EFL writing at the learner level as the capacity to analyse information critically, choose suitable AI tools, and make informed decisions on them during the writing task. Following this, [16] adds affective, behavioural, and cognitive aspects of the conceptualization of generative AI literacy, and [14] focuses on critical awareness, critical attitudes towards AI-generated outputs, strategic interaction with AI tools, and evaluating AI affordances and limitations. All these studies show that AI literacy is becoming more broadly defined as "the ability to engage with AI in a critical and responsible way. However, the correlation between AI literacy and students' epistemic processes and their capacity to critically assess AI-generated knowledge is not yet fully understood and can serve as a valuable foundation for future studies.

2.2. Epistemic Justification and Synthetic Knowledge Evaluation

As AI becomes more widely adopted in the educational setting, the question of how students evaluate the trustworthiness of AI-generated content, and its acceptance as legitimate knowledge, is becoming increasingly salient [18]. Epistemic justification is about the reasons the agent considers and attaches to his/her belief or judgment perhaps involving taking evidence into account, trustworthiness of evidence, logical consistency with the evidence, corroboration, and contextual relevance [19]. In university education, processes play a key role in the academic inquiry as it is expected that students differentiate claims that are plausible from well-founded ones. With generative AI's ability to generate coherent, fluent, contextually relevant responses, ensuring a response is both factual and well-supported becomes more complex. Students need to be able to challenge the underpinnings of AI-generated claims, to check information against reliable sources, and to assess whether AI-generated information evidence is adequate for academic acceptance. Epistemic Justification is therefore a crucial cognitive aspect of responsible interaction with AI generated information [20].

The importance of epistemic justification becomes particularly evident when considering the characteristics of synthetic knowledge. The trend of processing and recombining information in massive data sets is giving rise to the creation of explanations, abstract summaries, interpretations, arguments and all manner of informational goods by AI systems. This synthetic knowledge can offer students quick access to information, and could serve to assist in knowledge construction, learning and/or academic exploration [21]. Meanwhile, it’s sourced, which poses issues of accuracy and reliability, not just completeness, evidence, relevance, bias and contextual appropriateness [22]. Students must then assess the AI generated response's authenticity and trustworthiness – not just its fluency or perceived authority. This needs to be assessed and involve students comparing information with independent sources, finding inconsistencies, and assessing how far information created is suitable for academic purposes [23]. Synthetic knowledge evaluation spans beyond standard artificial intelligence applications, and in this advanced form of interaction, students not only use AI systems but also critically evaluate the quality and reliability of AI-generated content.

The connection between epistemic justification and synthetic knowledge evaluation is therefore conceptually significant. A student might have the technical skills to receive an answer from an AI system but may not necessarily have the skills to decide the quality or veracity of that answer [21]. On the other hand, by actively looking for evidence, critically assessing sources, challenging unsourced information and comparing information, students could potentially be better able to recognise flaws in the information produced by AI. Existing discussions of AI literacy similarly emphasize critical evaluation as an important higher-order capability. Unlike basic knowledge and application of AI, critical assessment is a crucial step in the process and is described differently from other uses, as elaborated by [18], and by [19] when emphasizing the importance of maintaining a critical distance from outputs generated by AI. The implications of these views is that synthetic knowledge assessment requires technological awareness expertise and epistemic judgment [23]. While past studies have mostly focused on AI literacy, AI application, and critical engagement as separate skills, have not yet examined the link between students' AI literacy and their assessment of synthetic knowledge through epistemic justification [20]. This under studied connection offers significant support to the value of analysing such constructs in an integrated empirical model.

2.3. Theoretical Foundation

The theoretical basis for the study is centred on a model of students' interaction with AI-generated knowledge, in which both technological and epistemic aspects of learner judgment are incorporated [24]. The concept of AI literacy grants students' knowledge about AI systems, their uses, potential, and limitations, as well as epistemic justification focuses on thinking processes used by students to identify whether information produced by AI systems can be believed and verified [25]. The ability to apply these understandings to assess AI-generated information is subsequently reflected in a synthetic knowledge test. This conceptualization posits that AI literacy is an important foundational competency, epistemic justification is an important evaluative process, and synthetic knowledge evaluation is a result of responsible use of AI-generated knowledge [26].

The framework of AI-literacy points put forth by [27], with components of knowing and understanding information about AI, using AI, critically assessing AI use, and AI ethics, is an important conceptual foundation for this relationship. The inclusion of higher-order evaluation is, especially for the current study, relevant. According to [28] the use of AI literacy should not be limited to lower order skills but extend critical evaluation of AI applications and informed judgment about the implications of their uses [29]. This is like the students' need to assess the trustworthiness of AI-generated content for specific tasks, as noted in the trial by [24]. This framework thus sets the ground for thinking of the concept of AI literacy in a way that goes beyond mere usage of technology to one of critical, responsible engagement with the output of AI.

Theoretical relationship as presented by [30] can therefore be encapsulated in a progressive process like this: Through AI literacy, one can understand the information generated by the AI, define epistemic justification as the grounds for accepting and questioning

the information, and with the ability of synthetic knowledge evaluation, ones assessment about the quality and suitability of the information generated by the AI [25]. This model acknowledges that students' ability to critique AI-generated content can be influenced by their conceptualizations and rationalizations of their evaluations of AI-made information [26]. The theoretical model thus exceeds a technology adoption notion and includes the ability to use cognitive and evaluative skills to engage in responsible academic work with AI [31]. Based on this, the present study investigates the structural relationship between AI Literacy and epistemic justification as well as synthetic knowledge assessment among university students.

2.4. Rationale for the Present Study

AI is changing the way university students interact with, understand, and create knowledge.AI is influencing the ways in which University users' access, interpret and build knowledge. While students may be ever more skilful using AI tools for academic tasks, effective engagement must go beyond mere technical competence to grapple with limitations of AI, substantiate information claims, and critically assess AI-produced knowledge. Hence, the understanding of AI literacy, epistemic justification, synthetic knowledge evaluation are significant and intertwined capabilities pertinent to responsible AI-based learning. Few systematic studies, however, have investigated these constructs in integrated investigations between university students. The study aims to fill this gap by testing of the relationships between AI literacy, epistemic justification, and synthetic knowledge evaluation, employing Structural Equation Modelling (SEM). It aims to describe the impact of students' AI-related skills on their critical evaluation and verification of AI-generated knowledge in post-secondary education.

3. Methods

3.1 Participants demographic characteristics

The demographic variables of the subjects were analysed to determine the make-up of the sample that was used in the current study. The sample comprised 350 students of university, from New Delhi was selected with stratified random sampling technique. For a descriptive profile of the participants the data emerging from the questionnaire was analysed in SPSS. The demographic characteristics were found to be relevant for "AI literacy", "epistemic justification", "synthetic knowledge evaluation", and "critical thinking disposition" responses of university students. The exploration of participant characteristics was then used as an overview of the sample prior to the examination of the relationships hypothesized in the structural model.

3.2 Data collection

A self-structured close-ended questionnaire was used to collect study data from university studies at New Delhi. Participants were selected using stratified random sampling technique and ultimately 350 university students were selected for the final sample. Primary data relating to the main constructs analysed in the study were collected from the selected respondents through a questionnaire. To ensure the data collection process to get the responses,

the data is collected related to the independent variables being AI literacy, mediating variables being epistemic justification, dependent variable being the synthetic knowledge evaluation, and moderated variable being critical thinking disposition of the proposed study model. Secondary data were also seen sufficient to complement the development of the study and review the conceptual framework for exploring the proposed relationships.

3.3 Instruments

A self-structured close-ended questionnaire was used as the major data-gathering tool in the study. The designed questionnaire was aimed at collecting data of the four constructs which have been included in the model. It was decided that AI literacy would serve as the independent variable, and epistemic justification would be the mediating variable used to measure the relation between AI literacy and the evaluation of synthetic knowledge. The dependent variable of knowledge evaluation was modelled as synthetic knowledge evaluation, as the dependent variable to be examined in the relationship with AI literacy and epistemic justification. An additional moderated variable (critical thinking disposition) was used to explore the moderated relationship between AI literacy and synthetic knowledge assessment. The questionnaire was thus constructed to elicit quantitative responses to the constructs and the relationships hypothesized from the study objectives.

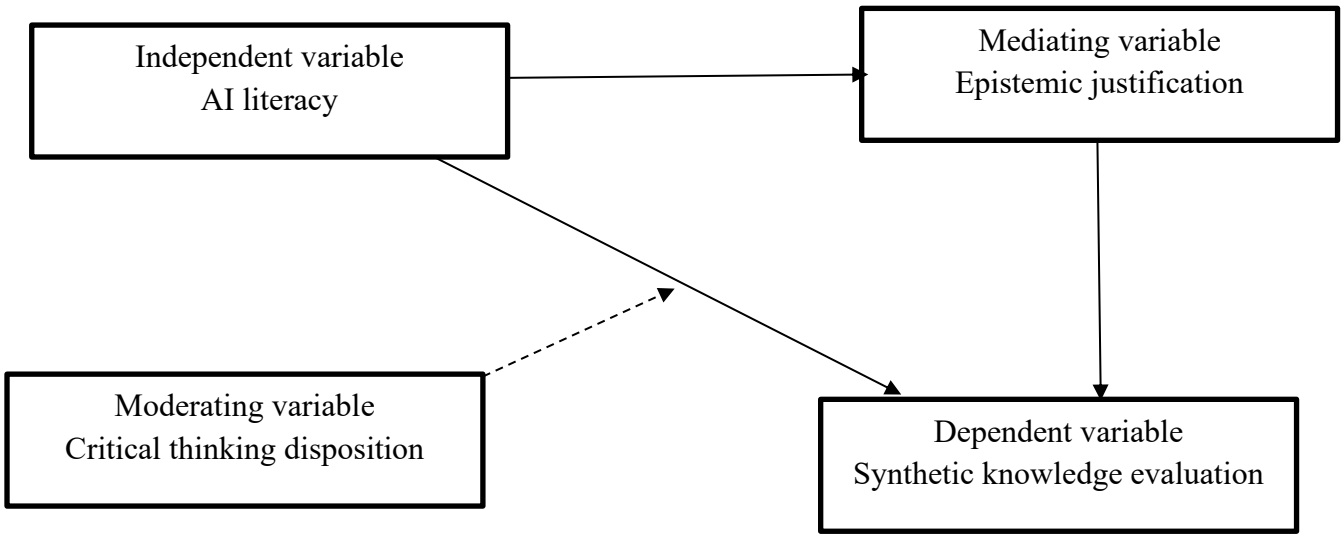


Figure 1: Conceptual model of the study ***Source: Authors own compilation***

3.4 Data analysis

Data collected were analysed with SPSS and SmartPLS 4. Demographic characteristics data of the respondents were analysed mainly using SPSS, while the data were analysed further using the Structural Equation Modelling (SEM) analysis using SmartPLS 4 software. To describe the study variables, Mean and Standard Deviation was used in the statistical analysis, then SEM to examine the proposed relationships in the conceptual model. The relationship between AI literacy and epistemic justification was explored in the structure analysis, as was

the relationship between epistemic justification and synthetic knowledge evaluation. Additionally, epistemic justification was explored as a mediator in the interaction between AI literacy and synthetic knowledge evaluation, and critical thinking disposition as a moderator in the interaction between AI literacy and synthetic knowledge evaluation. Therefore, the analytical method was directly focused on the study purposes and hypotheses and was performed with SmartPLS 4.

4. Results

4.1. Demographic variable of the respondents

Table 1: Demographic profile of the respondents

S.NO	Demographic characteristics		N	%
1	Age (in years)	18-20	76	21.7
		21-23	55	15.7
		24-26	69	19.7
		27-30	69	19.7
		Above 30	81	23.1
2	Gender	Female	178	50.9
		Male	172	49.1
3	Academic level	Undergraduate	108	30.9
		Postgraduate	124	35.4
		Doctoral	118	33.7
4	Primary academic use of generative AI	Academic writing	65	18.6
		Conceptual learning	59	16.9
		Information retrieval	84	24
		Problem solving	65	18.6
		Research support	77	22
5	Duration of generative AI experience	Less than 6 months	70	20
		6 months-1 year	77	22
		1-2 years	72	20.6
		2-3 years	69	19.7
		More than 3 years	62	17.7
6	Verification of AI generated information	Always	75	21.4
		Never	68	19.4
		Often	59	16.9
		Rarely	58	16.6
		Sometimes	90	25.7
7	Basis for evaluating AI-generated knowledge	Academic sources	67	19.1
		AI-generated response alone	71	20.3
		Expert verification	69	19.7
		Multiple credible sources	72	20.6
		Personal knowledge	71	20.3

4.2. Cumulative results based on hypotheses

The demographic profile of the students in the study (350 university students) is shown in Table 1. The age distribution reveals majority of age group above 30 years is 23.1% followed by 18-20 years age group. The female respondents make up 50.9% – with males accounting for 49.1%. 35.4% of postgraduate students, 33.7% of doctoral students and 30.9% of undergraduates make up the majority. The most frequent academic applications of the generative AI are for information retrieval (24%). When asked about the experience, 22% say 6 months – 1 year. 25.7% of participants confirm information generated by AI sometimes and 20.6% do so by evaluating it with multiple credible sources.

H1: AI literacy has a significant positive impact on epistemic justification, and epistemic justification has a significant positive impact on synthetic knowledge evaluation among university students.

H2: Epistemic justification significantly mediates the relationship between AI literacy and synthetic knowledge evaluation among university students.

H3: Critical thinking disposition significantly moderates the relationship between AI literacy and synthetic knowledge evaluation among university students.

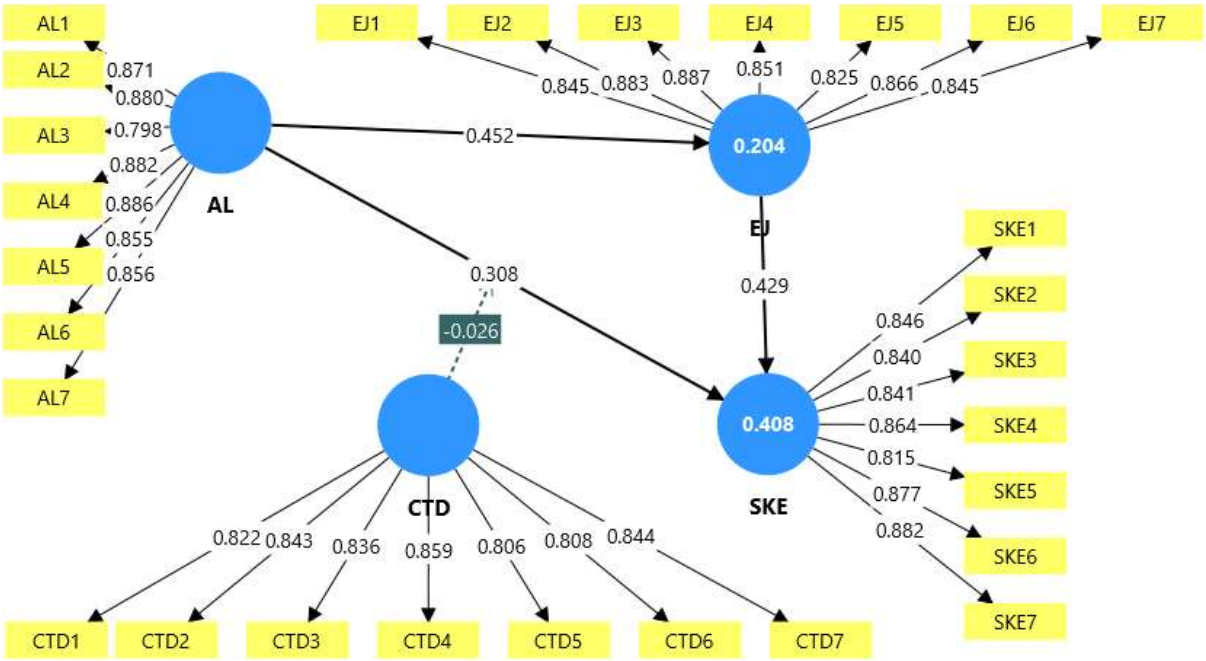


Figure 2: SEM Model

Source: Smart PLS

The structural model for the study of AI Literacy (AL), Epistemic Justification (EJ), Critical Thinking Disposition (CTD) and Synthetic Knowledge Evaluation (SKE) is shown in Figure 2. The findings show that AI Literacy has a positive influence on Epistemic Justification (β =

0.452), and that Epistemic Justification has a positive influence on Synthetic Knowledge Evaluation (β = 0.429). AI Literacy also shows positive direct correlation with knowledge evaluation by synthetic knowledge (β = 0.308), meaning that its direct contribution to students' knowledge evaluation generated by AI is evident. The model explains 20.4% of the variance in Epistemic Justification (R^2 = 0.204) and 40.8% of the variance in Synthetic Knowledge Evaluation (R^2 = 0.408). There is very small negative moderating effect of interaction (β = −0.026) between Critical Thinking Disposition and between AI Literacy and Synthetic Knowledge Evaluation.

Table 2: R-square

	R-square	R-square adjusted
EJ	0.204	0.202
SKE	0.408	0.401

Table 2 shows the explanatory power of the structural model of the endogenous constructs. The coefficient of determination R^2 for Epistemic Justification (EJ) is 0.204, meaning that AI Literacy accounts for 20.4% of the variance in EJ. The adjusted R^2 value is 0.202, close to the unadjusted value of 0.207, showing consistency of the model in explaining the data. In the latter, the mediational model for Synthetic Knowledge Evaluation (SKE) produces an adjusted R^2 of 0.401 and an R^2 of 0.408, indicating similar level of variance between each predictor and the model. The overall results indicate that the model explains more variance of Synthetic Knowledge Evaluation than Epistemic Justification.

Table 3: F-Square

	AL	CTD	EJ	SKE	CTD x AL
AL			0.256	0.123	
CTD				0.001	
EJ				0.223	
SKE					
CTD x AL				0.001	

The effect size (ES) of the predictor variables in the endogenous construct is provided in Table 3. Epistemic Justification shows contributions of AI Literacy with effect size of 0.123, which is measurement show the contribution of AI Literacy is measurable. The size of the contribution by Critical Thinking Disposition to the model is very small reflecting an effect size of 0.001. The effect size for Epistemic Justification is 0,223 corresponding to a relatively high association with Synthetic Knowledge Evaluation. The effect size for the interaction term CTD×AL is extremely small (-0.001), showing a very small amount of the variance explained by the moderating interaction. In general, the results show that the interaction effect between

Epistemic Justification and Critical Thinking Disposition has less impact on the endogenous outcome compared to Epistemic Justification.

Table 4: Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AL	0.942	0.945	0.953	0.742
CTD	0.926	0.931	0.940	0.691
EJ	0.940	0.941	0.951	0.736
SKE	0.937	0.938	0.949	0.726

Table 4 shows reliability and convergent validity of the constructs of the measurement model. Cronbach's alphas are from 0.926 to 0.942, and composite reliabilities (rho_a) are from 0.931 to 0.945. Likewise, composite reliability (rho_c) goes from 0.940 to 0.953 for each of the subscores for AL, CTD, EJ, and SKE. AVE range from 0.691 to 0.742 suggests that the constructs have good convergent construct validity. The findings suggest there is a good internal consistency of the items for the four constructs used, and there is a high AVE for items representing each construct, which reflects that the items cover the constructs. Therefore the reliability and convergent validity results displayed in Table 4 can be considered sufficient to be able to proceed with further analysis in hypotheses.

Table 5: Discriminant validity- HTMT matrix

	AL	CTD	EJ	SKE	CTD x AL
AL					
CTD	0.323				
EJ	0.476	0.422			
SKE	0.535	0.300	0.613		
CTD x AL	0.119	0.025	0.025	0.016	

Table 5 shows the discriminant validity of constructs according to Fornell-Larcker criterion in which the diagonal line shows the square root of AVE, and the off-diagonal line is the correlation between the constructs. The results show that the square root of AVE for AL is 0.535, for CTD is 0.323, for EJ is 0.476, and for SKE is 0.613. The correlations for the constructs range between 0.016 and 0.613, and the interaction construct CTD × AL ranges between 0.016 and 0.119 with the other constructs. The results show the level of association between the constructs giving evidence that confirms the degree of distinctiveness of the constructs in the measurement model.

Table 6: Discriminant validity- Fornell Larcker criterion

	AL	CTD	EJ	SKE
AL	0.862			
CTD	0.305	0.831		
EJ	0.452	0.397	0.858	
SKE	0.505	0.283	0.576	0.852

The discriminant validity of the constructs is reported in Table 6, in terms of the Heterotrait–Monotrait (HTMT) ratio. The HTMT values are 0.862 for AL, 0.831 for CTD, 0.858 for EJ, and 0.852 for SKE on the diagonal, while the inter-construct values range from 0.283 to 0.576. The correlation between AL and CTD is 0.305, between AL and EJ is 0.452 and between AL and SKE is 0.505. The values of CTD are 0.397 for EJ and 0.283 for SKE, while the values of EJ and SKE are 0.576. In general, the reported inter-construct values reveal different relationships between the constructs and show evidence of the validity assessment of the measurement model from a discriminant perspective.

Table 7: Discriminant validity- Cross loadings

	AL	CTD	EJ	SKE	CTD x AL
AL1	0.871	0.235	0.312	0.397	0.066
AL2	0.880	0.281	0.417	0.493	0.080
AL3	0.798	0.203	0.363	0.390	0.119
AL4	0.882	0.257	0.433	0.447	0.161
AL5	0.886	0.280	0.416	0.440	0.102
AL6	0.855	0.284	0.383	0.423	0.040
AL7	0.856	0.290	0.382	0.441	0.128
CTD1	0.207	0.822	0.296	0.198	0.026
CTD2	0.278	0.843	0.388	0.275	0.003
CTD3	0.245	0.836	0.318	0.240	0.054
CTD4	0.279	0.859	0.362	0.257	0.010
CTD5	0.261	0.806	0.282	0.221	-0.010
CTD6	0.240	0.808	0.327	0.203	-0.028
CTD7	0.252	0.844	0.321	0.237	0.011
EJ1	0.406	0.329	0.845	0.494	0.016
EJ2	0.436	0.372	0.883	0.490	-0.032
EJ3	0.379	0.377	0.887	0.498	-0.011
EJ4	0.393	0.315	0.851	0.505	0.003
EJ5	0.347	0.338	0.825	0.481	-0.030
EJ6	0.396	0.362	0.866	0.502	0.022
EJ7	0.349	0.290	0.845	0.489	-0.030
SKE1	0.443	0.233	0.490	0.846	-0.011
SKE2	0.427	0.174	0.446	0.840	0.013
SKE3	0.418	0.200	0.485	0.841	-0.007
SKE4	0.414	0.327	0.502	0.864	-0.002
SKE5	0.440	0.234	0.499	0.815	0.037
SKE6	0.444	0.243	0.503	0.877	-0.008
SKE7	0.424	0.275	0.508	0.882	0.015
CTD x AL	0.116	0.012	-0.010	0.006	1.000

Table 7 presents the outer loadings of the indicators associated with AI Literacy (AL), Critical Thinking Disposition (CTD), Epistemic Justification (EJ), and Synthetic Knowledge Evaluation (SKE). As can be seen from the results, the indicators have strong association with the constructed indicators. For AL, the outer loadings are between 0.798 and 0.886; the CTD indicators range from 0.806 to 0.859. Likewise, the range of EJ indicators is 0.825 to 0.887, and the range of SKE indicators is 0.815 to 0.882. These values in turn show that the indicators can adequately express their concepts. This is because the interaction between the two variables in the CTD model has Eigenvalue = 1.000, with a relatively low association with other constructs. Overall, the findings presented in Table 7 show satisfactory indicator-level measurement performance and justify the use of the indicators for further analysis of the structural model.

Table 8: Collinearity Statistic (VIF)- Outer model – List

	VIF
AL1	3.220
AL2	3.172
AL3	2.189
AL4	3.290
AL5	3.382
AL6	2.817
AL7	2.820
CTD1	2.472
CTD2	2.462
CTD3	2.496
CTD4	2.731
CTD5	2.268
CTD6	2.273
CTD7	2.617
EJ1	2.617
EJ2	3.312
EJ3	3.501
EJ4	2.688
EJ5	2.420
EJ6	3.007
EJ7	2.662
SKE1	2.675
SKE2	2.592
SKE3	2.612
SKE4	2.975
SKE5	2.285
SKE6	3.162
SKE7	3.333
CTD x AL	1.000

The Variance Inflation Factor (VIF) values of the indicators in the measurement model are presented in Table 8. The range of VIF values obtained for AI literacy is from 2.189-3.382 and

for critical thinking disposition is 2.268-2.731. The values for Epistemic Justification are between 2.420 and 3.501; and the same for Synthetic Knowledge Evaluation are 2.285 to 3.333. VIF of the interaction term CTD × AL is 1.000. The overall VIF values continue to stay in the range as reported in the model, with the highest VIF value reported for EJ3 (3.501). The results then give the collinearity statistics of the indicators and suggest to continue considering the constructs for further structural model assessment.

Table 9: Model fit

	Saturated model	Estimated model
SRMR	0.037	0.078
d_ULS	0.543	2.474
d_G	0.218	0.236
Chi-square	437.133	465.422
NFI	0.945	0.942

Table 9 reports the model fit indicators Standardized Root Mean Square Residual (SRMR), d_ULS, d_G, Chi-square and Normed Fit Index (NFI) for the structural model. The values for the SRMR are 0.037 for the saturated model and 0.078 for the estimated model, respectively, which are quite low and demonstrate a comparatively low degree of residual discrepancy between the observed and model-implied correlations. Using these models, the midpoint d_ULS values are 0.543 and 2.474 for the saturated and estimated models, respectively, and the d_G values are 0.218 and 0.236 for the saturated and estimated models, respectively. The Chi-square values of the saturated model are 437.133 and of the estimated model is 465.422 which indicate the difference between the empirical and model-implied covariance structure. Additionally, the NFI values are 0.945 and 0.942, respectively, which is considered to be a relatively high model fit. As a general rule, the findings as shown in Table 9 confirm that the proposed framework is also adapted well to the empirical data and is qualified for further investigation of the structural model.

5. Discussion

[32] investigates the relationship between AI Literacy and Epistemic Justification, Critical Thinking Disposition and the Synthetic Knowledge Evaluation among university students. The results show that significant positive correlations exist among the following pairs: AI Literacy and Epistemic Justification, as well as as Epistemic Justification and Synthetic Knowledge Evaluation. AI Literacy also shows a positive direct correlation with Synthetic Knowledge Evaluation, suggesting that a student's knowledge about AI is related to their knowledge assessment of artificial intelligence-generated knowledge [33]. The variance in the Epistemic Justification is explained by the structural model and the variance in the Synthetic Knowledge Evaluation [34] is explained by the structural model in a way of 40.8%. The results show that awareness of artificial intelligence's capabilities and limitations is required for appropriate interaction, as it demands that students be able to question, check, interpret and critically reflect on aggregated information [35].

The positive correlation between AI Literacy and Epistemic Justification (β = 0.452) means that the higher the level of AI literacy, the higher the engagement in evidence-based judgment [36]. Students with wider knowledge of AI systems, their capabilities, applications, and limitations might better assess the credibility and evidentially quality of AI-generated information [37]. This awareness can prompt learners to critically reflect on artificial intelligence output instead of blindly relying on it. AI Literacy has thus been identified as an important preliminary skill for developing epistemic judgment. This discovery indicates that knowledge about how AI works and its capabilities and constraints can impact the way students use information produced using AI technology [33]. Improving students' AI literacy skills could help them realize that claims made by AI are not automatically reliable, and that it should check what is true and verify those claims by comparing them to authoritative sources before using them in educational work [38].

The positive correlation of the relation between Epistemic Justification and Synthetic Knowledge Evaluation (beta = 0.429) suggests that in evaluating AI-generated knowledge, evidence-based reasoning plays an important role [39]. A student who has carried out systematic information analysis, considers the author's credibility, looks back at one's own information, compares alternate information, and recognizes inconsistencies might be better able to assess the accuracy and reliability of the information produced by their AI [40]. It sometimes seems rational, relevant and authoritative, yet it is not sufficiently supported by evidence [4]. Epistemic Justification is an important evaluative process in which students select information possessing reasonable support from information possessing good grounds for acceptance. The discovery has prompted a call for teachers to factor the capability of students in using AI tools into their assessment methods, while also allowing them to assess whether and what goes into or out of the information spiral created by such systems [42].

Adopting AI Literacy also shows a positive direct relationship with Synthetic Knowledge Evaluation with β = 0.308. The result implies that students' understanding of AI directly affects their ability to evaluate learning value and usefulness of AI-supported knowledge [38]. Students who know what AI can and cannot do, how it can be used effectively, but when such use may fail or be ineffective may be more vigilant when assessing the outputs of the AI to understand whether can be used in their academic work properly. The relationship shows that the understanding of technology and assessing knowledge is related, but not the same as competencies in AI-enabled learning [43]. Thus, AI literacy can aid students in understanding that artificial intelligence information should not be taken as gospel. The discovery also highlights a need for AI literacy: Make sure users learn how to be aware of, understand, evaluate, and engage responsibly with the information produced by AI [44].

The proposed mediating role of Epistemic Justification is reflected in the relationships observed within the structural model. AI Literacy has a positive correlation with Epistemic Justification, and Epistemic Justification has a positive correlation with Synthetic Knowledge Evaluation. Simultaneously, AI Literacy has positive feedback with Synthetic Knowledge Evaluation [39]. The pattern shows that learning AI literacy is directly linked with synthetic knowledge as well as its epistemic process in evaluating information. In the framework

proposed, Epistemic Justification can serve as an important connection point [36]. The reported results do not include an indirect-effect coefficient, significance value, or confidence interval for the mediation pathway, however. The available results thus reflect the relationships as hypothesized in the mediation model but are not statistically valid to support the significance of the indirect effect alone [41].

The interaction term Critical Thinking Disposition x AI Literacy indicates a β of −0.026 [43] against the Synthetic Knowledge Evaluation, and an f2 of 0.001. The small negative correlation suggests the interaction's effect was not very large when working with the relationship between AI Literacy and Synthetic Knowledge Evaluation [42]. Thus, within the proposed model, Critical Thinking Disposition makes a limited contribution because it interacts with AI Literacy. As revealed by the explanatory results, AI Literacy explains 20.4% of the variance in the Epistemic Justification, and the predictors explain 40.8% of the variance in the Synthetic Knowledge Evaluation [44]. Moreover, the model retrievals are SRMR 0.037 and NFI 0.945 for the saturated and estimated models respectively [45]. The overall results make a point of the value, interconnectedness and importance of technological understanding, epistemic judgment, and critical evaluation in supporting responsible use of AI-produced knowledge in higher education [37].

6. Conclusion

AI Literacy is situating itself as a key tool for fostering responsible interactions with AI among students at university. The results suggest that the higher students' level of AI Literacy, the higher their level of Epistemic Justification and – somewhat unsurprisingly – their Synthetic Knowledge Evaluation. Learning about the capabilities, applications, and limitations of AI and the information it generates help students think more critically about information created by AI and their ability to evaluate its academic appropriateness and authority. The results also showed that AI Literacy spills over into Synthetic Knowledge Evaluation, thereby establishing that knowledge of technology is a part of students' ability to evaluate synthetic knowledge. Beyond simply using AI tools, AI Literacy is crucial for educating oneself with AI-generated information in a thoughtful, critical, and ethical way.

The study would be of significance towards the higher education, teachers and academic programs. The results indicated that the capacities associated with epistemic reasoning and knowledge assessment should be included in education about AI technologies. Universities can promote students to check the credibility of the information source generated by AI, analyse the credibility of information sources, compare credible information, find potential limitations, and examine the proof of information generated by AI. There are opportunities to introduce aimed activities related to AI Literacy and Epistemic Justification in academic curricula and faculty development programs. Collectively, these practices in education can help students cultivate more responsible and informed attitudes toward using generative AI in their academic education, research, writing, and knowledge-building activities.

The study of Synthetic Knowledge Evaluation is analysed using quantitative and cross-sectional approach at university level particular focus areas are the University students of New Delhi. The findings presented may not apply to students in other geographic locations, institutions, disciplines, and environments because of this. The structured questionnaire provides measurable evidence in relation to the chosen constructs but does not provide much insight into students' reasoning processes in assessing AI generated information. The impact of Critical Thinking Disposition as a moderating construct in the model is also explored, and the findings show limited interaction effect. These restrictions should be considered when interpreting and implementing the findings beyond the frame of the study conducted in the present study.

Further study can be conducted based on the proposed architecture in different geographic regions, universities, academic fields, and student groups to gain a broader contextual understand of the proposed architecture. Longitudinal studies could investigate the evolution of AI Literacy, Epistemic Justification, Critical Thinking Disposition, and Synthetic Knowledge Evaluation as students' exposure to generative AI continues. Further investigations using more mixed methods can explore how students' reason in verifying and evaluating AI-generated data. There are also opportunities for further study that could extend the explanatory range of the framework by adding other aspects of students' experiences of AI, and their knowledge practices. The study can help to integrate into the greater understanding of responsible engagement with AI and in the development of effective education strategies for evaluating synthetic knowledge.

Reference

[1] Xie, X., M. F. Teng, L. J. Zhang, and A. Alamer. "Exploring AI Literacy and AI-Induced Emotions among Chinese University English Language Teachers: The Partial Least Square Structural Equation Modeling (PLS-SEM) Approach." *International Journal of Applied Linguistics* 35, no. 4 (2025): 1897–1911.

[2] Kurniati, E., I. Emaliana, and R. Sahar. "Empathy and Epistemic Beliefs Empower Critical, Culturally Responsive ChatGPT Integration in Learning English Academic Writing." *Cogent Education* 12, no. 1 (2025): 2590919.

[3] Panagopoulos, E., C. M. Liapis, A. Adamopoulou, I. Kamarianos, and S. Kotsiantis. "Trust, Education, and Artificial Intelligence: Adoption, Explainability, and Epistemic Authority among Teacher-Education Undergraduates in Greece." *Algorithms* 19, no. 5 (2026): 350.

[4] Nykyporets, S. S., and N. M. Hadaichuk. "Foreign Language Media Literacy as a Protective Factor against AI-Generated Disinformation and Psychological Stress in Technical Higher Education in Ukraine." In Transformational Vectors of Public Administration, Law, and Humanities in the Development of the Modern Educational System, 305–330, 2025.

[5] Muis, K. R., M. Chevrier, C. A. Denton, and K. M. Losenno. "Epistemic Emotions and Epistemic Cognition Predict Critical Thinking about Socio-Scientific Issues." *Frontiers in Education* 6 (2021): 669908.

[6] Kelly, M. "Epistemology, Epistemic Belief, Personal Epistemology, and Epistemics: A Review of Concepts as They Impact Information Behavior Research." *Journal of the Association for Information Science and Technology* 72, no. 4 (2021): 507–519.

[7] Rožanec, J., E. Trajkova, I. Novalija, P. Zajec, K. Kenda, B. Fortuna, and D. Mladenić. "Enriching Artificial Intelligence Explanations with Knowledge Fragments." *Future Internet* 14, no. 5 (2022): 134.

[8] Futia, G., and A. Vetrò. "On the Integration of Knowledge Graphs into Deep Learning Models for a More Comprehensible AI—Three Challenges for Future Research." *Information* 11, no. 2 (2020): 122.

[9] Long, D., and B. Magerko. "What Is AI Literacy? Competencies and Design Considerations." In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. 2020.

[10] Schnatz, N. I., and A. Bieri. "From AI Literacy to Epistemic Agency: How GenAI Re-Shapes Writing Pedagogy in Engineering Education." *MedienPädagogik: Zeitschrift für Theorie und Praxis der Medienbildung* 71 (2026): 319–341.

[11] Chiu, T. K., Z. Ahmad, M. Ismailov, and I. T. Sanusi. "What Are Artificial Intelligence Literacy and Competency? A Comprehensive Framework to Support Them." Computers and Education Open 6 (2024): 100171.

[12] Chee, H., S. Ahn, and J. Lee. "A Competency Framework for AI Literacy: Variations by Different Learner Groups and an Implied Learning Pathway." British Journal of Educational Technology 56, no. 5 (2025): 2146–2182.

[13] Tenberga, I., and L. Daniela. "Artificial Intelligence Literacy Competencies for Teachers through Self-Assessment Tools." Sustainability 16, no. 23 (2024): 10386.

[14] Mikeladze, T., P. C. Meijer, and R. P. Verhoeff. "A Comprehensive Exploration of Artificial Intelligence Competence Frameworks for Educators: A Critical Review." *European Journal of Education* 59, no. 3 (2024): e12663.

[15] Stolpe, K., and J. Hallström. "Artificial Intelligence Literacy for Technology Education." *Computers and Education Open* 6 (2024): 100159.

[16] Al-Abdullatif, A. M. "Auditing AI Literacy Competency in K–12 Education: The Role of Awareness, Ethics, Evaluation, and Use in Human–Machine Cooperation." *Systems* 13, no. 6 (2025): 490.

[17] Zhou, X., Y. Li, C. S. Chai, and T. K. Chiu. "Defining, Enhancing, and Assessing Artificial Intelligence Literacy and Competency in K–12 Education from a Systematic Review." *Interactive Learning Environments* 33, no. 10 (2025): 5766–5788.

[18] Nasho Ah-Pine, E., and I. S. Awuye. "Exploring the Trustworthiness of ChatGPT: How Students Perceive AI Reliability in a Business School Context." *Journal of International Education in Business* (2025).

[19] Ebrahimian, S. R. M. "Explaining the Process of University Students' Epistemic Trust in AI-Generated Content: A Grounded Theory Study from the Perspective of Philosophy of Education." *Iranian Journal of Educational Sociology* (2026): 1–21.

[20] Brown, A. K. "Exploring Generative Artificial Intelligence Perceptions and Information Retrieval Behaviors among Students: An Investigation of Google Search and ChatGPT Queries." 2026.

[21] Batista, J., A. Mesquita, and G. Carnaz. "Generative AI and Higher Education: Trends, Challenges, and Future Directions from a Systematic Literature Review." *Information* 15, no. 11 (2024): 676.

[22] Elsayed, H. "The Impact of Hallucinated Information in Large Language Models on Student Learning Outcomes: A Critical Examination of Misinformation Risks in AI-Assisted Education." *Northern Reviews on Algorithmic Research, Theoretical Computation, and Complexity* 9, no. 8 (2024): 11–23.

[23] Lee, A. V. Y., S. C. Tan, and C. L. Teo. "Designs and Practices Using Generative AI for Sustainable Student Discourse and Knowledge Creation." *Smart Learning Environments* 10, no. 1 (2023): 59.

[24] Jose, B., A. Cleetus, B. Joseph, L. Joseph, B. Jose, and A. K. John. "Epistemic Authority and Generative AI in Learning Spaces: Rethinking Knowledge in the Algorithmic Age." *Frontiers in Education* 10 (2025): 1647687.

[25] Suazo Galdames, I. C., M. Santiesteban Velázquez, M. Saracostti, and A. M. Chaple Gil. "Between Cognitive Offloading and Critical Autonomy: A Systematic Review of the Epistemic Implications of Generative AI in Higher Education." *Frontiers in Education* 11 (2026): 1878665.

[26] Rind, I. A., J. Bhatti, and K. Chellappan. "From Blind Trust to Critical Inquiry: Epistemic Beliefs and Student Engagement with ChatGPT in Higher Education." *Jurnal Kejuruteraan* 38, no. 1 (2026): 1–14.

[27] Isaeva, R., H. N. Caner, M. Caner, L. Giray, and E. Karadag. "Students' Engagement with Generative AI in Academic Learning: A Self-Determination Theory and Epistemic Network Analysis Study." *Computers and Education: Artificial Intelligence* (2026): 100606.

[28] Du, Y., and Y. Yuan. "Epistemic Dependence in AI-Mediated Learning." AI & Society (2026): 1–11.

[29] Olaniyan, Y. D., M. O. Martins, and R. H. Al Maqrashi. "Generative Artificial Intelligence and Epistemic (In)Justice: Perspectives from Higher Education Students in the Global North and South." *Frontiers in Human Dynamics* 8 (2026): 1790324.

[30] Khatun, A., and S. M. Shoshe. "From Empathy to Algorithm: What Remains Human in AI-Mediated Education Fields." 2023.

[31] Bantjes, R. "The Epistemic Crisis of Liberalism and the Rise of the Far Right." In *Political Ecologies of the Far Right*, Lund, Sweden, 2019.

[32] Kiili, C., I. Bråten, and J. Coiro. "The Framework of Prior Knowledge in Online Credibility Evaluation." *Educational Psychologist* (2026): 1–21.

[33] dos Santos, J. A. "Information and Algorithmic Literacy in the Age of Artificial Intelligence: Challenges and Pedagogical Practices in Secondary Education at Porto." 2026.

[34] Johri, A. "Augmented Sociomateriality: Implications of Artificial Intelligence for the Field of Learning Technology." *Research in Learning Technology* 30 (2022).

[35] Raphael, E. A., and U. E. Amoji. "Epistemic Opportunities and Challenges in Artificial Intelligence." *KIU Interdisciplinary Journal of Humanities and Social Sciences* 6, no. 2 (2025): 10–21.

[36] Dahlkemper, M. N., S. Z. Lahme, and P. Klein. "How Do Physics Students Evaluate Artificial Intelligence Responses on Comprehension Questions? A Study on the Perceived Scientific Accuracy and Linguistic Quality of ChatGPT." Physical Review Physics Education Research 19, no. 1 (2023): 010142.

[37] Bozkurt, A., X. Junhong, S. Lambert, A. Pazurek, H. Crompton, S. Koseoglu, et al. "Speculative Futures on ChatGPT and Generative Artificial Intelligence (AI): A Collective Reflection from the Educational Landscape." *Asian Journal of Distance Education* 18, no. 1 (2023): 53–130.

[38] Zhou, J., Y. Zhang, Q. Luo, A. G. Parker, and M. De Choudhury. "Synthetic Lies: Understanding AI-Generated Misinformation and Evaluating Algorithmic and Human Solutions." In Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, 1–20. 2023.

[39] Fui-Hoon Nah, F., R. Zheng, J. Cai, K. Siau, and L. Chen. "Generative AI and ChatGPT: Applications, Challenges, and AI-Human Collaboration." *Journal of Information Technology Case and Application Research* 25, no. 3 (2023): 277–304.

[40] Kim, J., H. Lee, and Y. H. Cho. "Learning Design to Support Student-AI Collaboration: Perspectives of Leading Teachers for AI in Education." *Education and Information Technologies* 27, no. 5 (2022): 6069–6104.

[41] How, M. L., and W. L. D. Hung. "Educing AI-Thinking in Science, Technology, Engineering, Arts, and Mathematics (STEAM) Education." *Education Sciences* 9, no. 3 (2019): 184.

[42] Dai, Y., C. S. Chai, P. Y. Lin, M. S. Y. Jong, Y. Guo, and J. Qin. "Promoting Students' Well-Being by Developing Their Readiness for the Artificial Intelligence Age." Sustainability 12, no. 16 (2020): 6597.

[43] Kreps, S., R. M. McCain, and M. Brundage. “All the News That’s Fit to Fabricate: AI-Generated Text as a Tool of Media Misinformation.” Journal of Experimental Political Science 9, no. 1 (2022): 104–117.

[44] Li, X., M. Y. C. Jiang, M. S. Y. Jong, X. Zhang, and C. S. Chai. “Understanding Medical Students’ Perceptions of and Behavioral Intentions toward Learning Artificial Intelligence: A Survey Study.” International Journal of Environmental Research and Public Health 19, no. 14 (2022): 8733.

[45] Yue, M., M. S. Y. Jong, and Y. Dai. “Pedagogical Design of K–12 Artificial Intelligence Education: A Systematic Review.” *Sustainability* 14, no. 23 (2022): 15620.

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