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Short Paper

Generative AI Usage, Critical Thinking, and Learning Engagement: A Correlational Study of Undergraduate Students in Henan Regional Universities, China

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Abstract

Purpose – Generative artificial intelligence (GenAI) is rapidly permeating university campuses, yet its relationships with critical thinking and learning engagement remain underexplored in China's regional universities. This study examined associations among undergraduates' GenAI usage behaviours, critical thinking dispositions, and learning engagement.

Method – A descriptive-correlational design was employed with 360 full-time undergraduates from three local universities in Henan Province. Validated instruments measured GenAI usage (frequency, context, purpose, method), five critical thinking dimensions, and three learning engagement dimensions. Pearson product–moment correlation analysis was used to examine the associations among the study variables.

Results – Students exhibited high-frequency but low-depth GenAI usage. Quality of engagement (context, purpose, method) was positively associated with analytical skill, systematic skill, inquisitiveness, and all learning engagement dimensions, but negatively correlated with truth-seeking and cognitive maturity. Usage frequency showed weak or non-significant associations.

Conclusion – How students engage with GenAI, rather than how often, is the critical factor influencing educational outcomes, with potential trade-offs in cognitive dispositions.

Recommendations – GenAI literacy could emphasise purposeful, critical use. Teachers are encouraged to design activities guiding reflective AI engagement. Institutions may consider developing clear guidelines for responsible integration.

Research Implications – The study contributes localised empirical evidence on the quality–outcome relationships of GenAI usage and offers a foundation for future research on intentional GenAI engagement in regional higher education.

Practical Implications – Universities should embed AI literacy in first-year curricula, using structured verification tasks; teachers should model critical AI use in assignments requiring synthesis rather than reproduction.

Keywords – generative artificial intelligence (GenAI), GenAI usage behaviour, critical thinking, learning engagement, undergraduate students

INTRODUCTION

Generative artificial intelligence (GenAI) has been advancing swiftly, reaching the status of a widespread teaching aid in universities worldwide. By utilising large language models, many undergraduate students have employed GenAI tools for various academic tasks, such as writing assignments, conducting research, explaining concepts, and generating ideas. Students began using these tools before universities could develop clear policies or training programs. As a result, most learned through trial and error rather than structured guidance (Gerlich, 2025).

Current research offers conflicting views on GenAI's educational effects. Proponents argue that AI assistance should be designed to help eliminate cognitive obstacles, provide instant responses, and support deeper thinking activities (Dwivedi et al., 2023). Critics, however, contend that overreliance on AI technology weakens students' active participation in learning, reduces their capacity for autonomous thought, and hinders deeper exploration of educational problems (Haensch et al., 2023). Despite these divergent perspectives, two significant gaps remain in the existing literature.

First, most studies focus on Western universities or China's top-tier 'Double First-Class' institutions, leaving regional universities understudied. Universities in Henan Province, for instance, generally lack robust digital literacy support, operate with large class sizes, and maintain inflexible rules for integrating artificial intelligence. Consequently, whether findings obtained under well-resourced conditions can be directly generalised to such contexts remains uncertain.

Second, most studies reduce GenAI usage to a one-dimensional frequency metric, thereby neglecting differences in usage context, purpose, and approach from learners' perspectives. For example, employing GenAI for fact-checking and idea exploration may foster critical thinking, whereas passive absorption of unmodified AI output likely promotes superficial cognitive processing. Moreover, few studies have simultaneously examined how multifaceted patterns of GenAI usage behaviour connect with critical thinking dispositions and learning engagement; this intersection remains insufficiently explored.

In response to these gaps, this study aims to examine the relationships among multidimensional GenAI usage behaviour (frequency, context, purpose, and method), critical thinking dispositions, and learning engagement among undergraduate students at local universities in Henan Province, China. The originality of this research lies in three aspects: (1) it provides empirical evidence from an underrepresented institutional context—local regional universities in central China—thereby extending the geographic and institutional scope of the AI-in-education literature; (2) it adopts a multidimensional conceptualisation of GenAI usage that moves beyond simple frequency counts to encompass context, purpose, and method, offering a more nuanced understanding of how students interact with these tools; and (3) it simultaneously investigates the associations between GenAI usage patterns and two key educational outcomes—critical thinking dispositions and learning engagement—within a single analytical framework, enabling an integrated assessment of GenAI's conditional and dimension-specific effects.

The theoretical framework of this study draws upon two established theories. Critical Thinking Disposition Theory (Facione, 1990) provides the conceptual foundation for understanding students' habitual inclinations toward truth-seeking, analytical skill, systematic skill, cognitive maturity, and inquisitiveness. Facione (1990) argued that critical thinking involves not just ability but disposition—the habitual inclination to question and reason. This distinction matters for GenAI usage: students with stronger dispositions may scrutinize AI-generated content, while others may accept it at face value. Self-determination theory (Ryan & Deci, 2000) underpins the learning engagement component of this study. This theory posits that human motivation and engagement are driven by the satisfaction of three basic psychological needs: autonomy (the need to experience self-directed behaviour), competence (the need to feel effective in one's activities), and relatedness (the need to feel connected to others). In educational settings, these needs correspond closely to the behavioural, cognitive, and emotional dimensions of learning engagement. Together, these two theories provide a coherent explanatory framework for understanding how different patterns of GenAI usage may either support or undermine students' critical thinking tendencies and their motivational engagement with learning.

Based on this theoretical grounding, the following research questions are addressed:

1. What are the self-reported patterns of GenAI usage behaviour among undergraduate students in terms of frequency, context, purpose, and method?
2. What are students' self-assessed levels of critical thinking dispositions across the dimensions of truth-seeking, analytical skill, systematic skill, cognitive maturity, and inquisitiveness?
3. What relationships exist between different dimensions of GenAI usage behaviour and critical thinking dispositions?
4. What relationships exist between different dimensions of GenAI usage behaviour and students' behavioural, cognitive, and emotional engagement in learning?

This study employs a descriptive-correlational research design. Data were collected from 360 full-time undergraduate students across three representative local universities in Henan Province. Validated instruments were used to assess four dimensions of GenAI usage, five dimensions of critical thinking, and three dimensions of learning engagement. Descriptive statistics and Pearson product–moment correlation coefficients were computed for data analysis.

As an exploratory investigation, this study provides specific empirical evidence on how students at regional universities in China are using GenAI tools. The findings may help students reflect on their own usage patterns and offer teachers practical reference points for guiding responsible GenAI integration. Furthermore, this study provides a foundation for subsequent research on GenAI application in similar local-university contexts.

LITERATURE REVIEW

GenAI Usage

GenAI tools have diffused rapidly through universities, but this adoption has been driven primarily by students rather than institutional planning. Gerlich (2025) found that most students learned GenAI usage through trial and error, without structured guidance. Raman et al. (2024) documented similarly high adoption rates coupled with low formal training. Brachman et al. (2024) went further, decomposing usage into multi-dimensional constructs—context, method, and purpose—and distinguishing efficiency-oriented goals like verification from comprehension-oriented goals like exploring alternative perspectives. This framework challenges the common reduction of GenAI usage to simple frequency counts (Strzelecki, 2024; Abbas et al., 2024).

The regional university context introduces additional complexity. In Henan Province, digital infrastructure is unevenly distributed, faculty-student ratios are high, and AI literacy support lags behind elite institutions. Li (2003) noted that Chinese educational contexts emphasize collective learning and respect for established knowledge, which may shape how students interact with AI-generated content differently from Western individualistic norms. Whether findings from well-resourced settings generalize to such conditions remains untested.

Critical Thinking Framework

Critical thinking research offers a lens for examining these interactions. Facione (1990) established the foundational framework, identifying seven core dispositions, which were subsequently operationalized through the California Critical Thinking Disposition Inventory (CCTDI). Peng et al. (2004) adapted this instrument for Chinese contexts, creating the CTDI-CV. The present study draws on the CTDI-CV but retains five dimensions most relevant to AI-mediated learning: truth-seeking, analytical skill, systematic skill, cognitive maturity, and inquisitiveness. Open-mindedness was excluded due to its substantial overlap with cognitive maturity ($r > 0.70$, Peng et al., 2004), and self-confidence was omitted as it operates as a metacognitive outcome rather than a dispositional antecedent (Facione, 2000). This focused approach aligns with Dwyer et al. (2014) and Niu et al. (2013), who demonstrated that targeted assessments yield clearer insights than comprehensive scales.

Kasneci et al. (2023) argued that large language models such as ChatGPT can support learning, but students must critically evaluate AI-generated information and verify outputs rather than accepting them uncritically. They emphasized that critical thinking and human judgment remain essential in AI-mediated learning. Similar concerns have also been raised in Chinese higher education. Han (2025) argued that the educational value of generative AI depends on students' ability to maintain critical thinking, reflective judgment, and independent verification rather than relying uncritically on AI-generated content. However, Abbas et al. (2024) documented the phenomenon of "cognitive offloading," in which students under heavy workloads delegate cognitive effort to AI, potentially weakening truth-seeking when they fail to detect biases or hallucinations (Ji et al., 2023). Larson et al. (2024) further proposed that effective human–AI collaboration requires an iterative cycle of questioning, generation, verification, and integration rather than a linear process of evaluation.

Learning Engagement: Cognitive, Behavioural, and Emotional Dimensions

Learning engagement theory provides a complementary framework. Fredricks et al. (2004) established the widely adopted three-dimensional model of learning engagement, encompassing behavioural, cognitive, and emotional engagement. Subsequent research has further emphasized that learning engagement is a multidimensional and context-dependent construct whose behavioural, cognitive, and emotional dimensions interact dynamically across different learning environments (Sinatra et al., 2015). Self-determination theory further explains these dimensions by proposing that engagement is fostered through the satisfaction of three basic psychological needs: autonomy, competence, and relatedness (Ryan & Deci, 2000). However, regional universities often face challenges such as large class sizes and rigid curricula, which may increase students' academic workload and reduce opportunities for autonomous learning. Previous research has shown that academic workload is more likely to lead to stress under unfavorable learning conditions, thereby undermining students' engagement and well-being (Koudela-Hamila et al., 2022). AI's effects on these dimensions appear mixed. Dwivedi et al. (2023) argued that generative AI can support students' deeper learning and understanding, whereas Abbas et al. (2024) described "thinking outsourcing," whereby students delegate cognitive activities to AI rather than constructing knowledge independently. Haensch et al. (2023) documented the "effort paradox," suggesting that although AI lowers initial learning barriers, it may also reduce students' willingness to persist through challenging tasks. Similarly, Chan et al. (2023) suggested that AI may alleviate frustration and sustain learning motivation when used appropriately; however, flow theory implies that excessive reductions in perceived challenge may ultimately diminish students' intellectual satisfaction and emotional engagement.

Contextual Gaps: Regional Chinese Universities

Most critically, current research primarily focuses on Western contexts or world-renowned universities, leaving a gap in studies concerning regional and local institutions. Yet GenAI tools have already permeated these campuses. Students in Henan Province use GenAI at rates comparable to their elite counterparts—often daily—but without the structured support, digital literacy workshops, or clear institutional policies that frame usage elsewhere. This disconnect between widespread adoption and absent research creates a blind spot: we know how students at well-resourced universities interact with AI, but not how those in regional institutions with uneven infrastructure, larger classes, and fewer individualized learning opportunities navigate these tools.

METHODOLOGY

Research Design

This study employs a descriptive-correlational design to examine associations among GenAI usage, critical thinking, and learning engagement. Given that the study aimed to explore the current state of GenAI application among undergraduates at local universities in Henan Province, a descriptive-correlational design was considered appropriate. Moreover, this paper conducts an investigation into whether associations exist between students' critical thinking dispositions and learning engagement levels. By collecting data on students' actual use of GenAI on campus, the study seeks to accurately describe the real situation of GenAI-assisted learning in a local university environment.

Research Variable and Definition

Within a post-positivist framework, critical thinking and learning engagement were treated as measurable constructs. Critical thinking was assessed across five dimensions—truth-seeking, analytical skill, systematic skill, cognitive maturity, and inquisitiveness—while learning engagement was assessed across three dimensions: behavioural, cognitive, and emotional engagement. A cross-sectional approach was adopted to gather quantitative data from participants at a single point in time through a standardised questionnaire. As a correlational study, it presents an orderly, empirically grounded account of the quantitative relationships among three sets of factors: multidimensional GenAI usage, critical thinking dispositions, and learning engagement.

Participants and Sampling

Using G-Power 3.1, the pre-specified sample size of this study follows established quantitative survey research guidelines.

Table 1. Parameters for Sample Size Determination

Parameter	**Statistical Tool**	**Effect Size (f2)**	**Significance Level (α)**	**Statistical Power**	**Minimum Item to Subject Ratio**	**Target Sample Size**
Value	G*Power 3.1	0.15(Medium)	0.05	0.95	1:5	360

Source: Authors' own work

According to Table 1, based on a moderate effect size (f2=0.15), set at a significance level α=0.05, with an anticipated power of 0.95, the final sample size of 360 participants fully satisfied this statistical requirement, as well as the minimum 1:5 item-to-subject ratio recommended for psychological scale validation.

To draw a representative sample of the local higher education system in Henan Province, three local universities across different locations of the province were selected through stratified convenience sampling: Henan University of Urban Construction (HUUC), Shangqiu Normal University (SQNU) and Zhengzhou Sias University (ZSU). HUUC is a publicly funded institution specializing in science and engineering education; SQNU has spent decades as a teacher-training university and now provides comprehensive academic programs; and as a private university, ZSU offers students an internationalized education focus. Selecting one engineering-focused public university, one comprehensive teacher-training university, and one private internationalized university allowed us to capture diverse student populations. The range of participant diversity was enhanced through recruitment using faculty networks alongside student counselling offices and university digital bulletin boards.

To ensure a homogeneous sample, reliable data, and adherence to ethical standards, the following criteria were applied. Inclusion criteria: (1) Full-time undergraduate students between the ages of 18 and 28 enrolled in Years 1-4; (2) Voluntarily participated in this study. Exclusion Criteria: Graduate students, part-time adult learners, students under academic warning, and those who could not finish the entire questionnaire were excluded because their academic backgrounds and context of using GenAI are quite different from the target undergraduate group.

Instruments

The questionnaire comprised four sections: basic information (3 items), GenAI usage (4 dimensions, 16 items), critical thinking (5 dimensions, 50 items), and learning engagement (3 dimensions, 15 items). All items were measured on a six-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree), with no neutral midpoint. Scores were divided into six equal-width interpretive intervals: 1.00–1.82 (very low), 1.83–2.66 (low), 2.67–3.49 (slightly low), 3.50–4.32 (slightly high), 4.33–5.16 (high), and 5.17–6.00 (very high).

The GenAI usage questionnaire was developed for the present study based on previous theoretical and empirical research on university students' use of generative AI (Brachman et al., 2024; Abbas et al., 2024). Guided by the existing literature, four dimensions—frequency, context, purpose, and method of use—were identified to characterize students' GenAI usage and operationalized into a 16-item questionnaire (four items per dimension). Branching logic directed respondents who had never used GenAI tools to skip this section. A sample context item is: "I use Generative AI tools to support my independent research, such as literature searches or exploring new topics."

Critical thinking disposition was assessed using an adapted version of the Chinese Critical Thinking Disposition Inventory (CTDI-CV; Peng et al., 2004). The original instrument comprises seven dimensions. Given the study's focus on AI-mediated learning, five dimensions—truth-seeking, analytical skill, systematic skill, cognitive maturity, and inquisitiveness—were selected, resulting in a total of 50 items (10 items per dimension). Open-mindedness was excluded because of its substantial conceptual overlap with cognitive maturity ($r > 0.70$; Peng et al., 2004), while self-confidence was omitted because it primarily reflects metacognitive confidence rather than dispositional critical thinking (Facione, 2000). A sample truth-seeking item is: "When facing controversial issues, I carefully consider multiple perspectives before forming my opinion" (reverse-scored).

The learning engagement questionnaire was developed based on the multidimensional framework proposed by Fredricks et al. (2004). Following their conceptualization of learning engagement, 15 items were constructed to measure behavioural, cognitive, and emotional engagement (five items per dimension). Sample items include: "I participate more actively in class discussions" (behavioural); "I critically evaluate whether explanations or answers make sense" (cognitive); and "I experience a sense of accomplishment when I overcome learning difficulties" (emotional).

Items were translated into Chinese using a translation-back-translation procedure. Two bilingual scholars in educational psychology produced independent forward translations; a professional translator then back-translated the reconciled version into English to check semantic consistency. Discrepancies in AI-related terminology were resolved through team discussion to ensure natural Chinese expression comprehensible to undergraduates. Three experts in educational technology and psychology assessed content validity by rating each item for relevance, clarity, and conciseness. Feedback was incorporated before finalizing the items.

The instruments were empirically validated through a pilot study with 30 undergraduate students enrolled at a typical local university in Henan. Reliability analysis confirmed good internal consistency for each key component. Cronbach's alpha coefficients for the critical thinking disposition subscales ranged from 0.82 to 0.88; the alpha coefficient for the total learning engagement scale was 0.89. The GenAI usage dimensions also showed acceptable internal consistency ($\alpha > 0.80$). Pilot participants further verified that the six-point scale was intuitive and that the branching survey logic functioned correctly for respondents with different AI usage experiences. These first-stage indicators confirmed the instruments to be both valid and reliable for subsequent data acquisition. In the formal test ($N = 360$), overall reliability proved satisfactory ($\alpha = 0.895$). By dimension: GenAI usage $\alpha = 0.877–0.879$; critical thinking $\alpha = 0.878–0.920$; learning engagement $\alpha = 0.876–0.877$.

Data Collection

Data were collected in three successive stages to ensure the legitimacy and credibility of the data. Before formal distribution, ethical approval of the study plan had been obtained. The questionnaire was converted into an electronic version using Tencent Questionnaire, which is commonly used to create surveys in Chinese scholarly works. The logical branch skipped the unselected scale items for users of GenAI; forced responses were used in essential items to reduce incomplete cases. All participants reviewed and gave explicit informed consent in the landing area, stating that they had understood: Anonymity; Voluntary participation; The right to withdraw at any time.

Formal data collection was conducted during the middle of the academic semester, when students were on campus and in a regular learning state; at this time, course workloads and students' motivation tended to be more stable and reflective of regular study states. Survey links and QR codes were distributed via several paths: instructor surveys within general-education courses; student-counseling activities targeting students of varying grades; and Academic Study Groups on WeChat. To reduce social desirability bias, when recruiting respondents, they were informed beforehand that this study only recorded their real-life learning activities without evaluating academic performance or specifying individual rights and responsibilities during participation in the questionnaire collection process.

Upon completion of data collection, a rigorous multi-stage quality control procedure was applied to filter invalid responses. Quickly filled-out questions within the first minute were not included in the statistics. This removed cases of uniformity in both scale-averaged and mean-scaled forms. Two embedded attention check items were used to identify inattentive responding, and logical consistency between self-reported GenAI frequency and actual usage contexts was further verified. Only those responses that met all quality control criteria were deemed valid; thus, these would form the basis for conducting statistical analysis.

Data Analysis

Data analysis was conducted in a sequential manner aligned with the study objectives, with strict adherence to analytical standards. First, an initial data screening checked for missing values and outliers as well as distributional properties. The online survey's forced-response settings minimized missing data, so all incomplete responses were eliminated by listwise deletion. The main variables' normality was tested by calculating their skewness and kurtosis statistics. Distributions were considered acceptable for parametric analysis, supporting the use of Pearson product–moment correlation coefficients for the correlation analyses. Cronbach's α was used to evaluate each scale's internal consistency. The descriptive statistical analysis involved the calculation of means and standard deviations for multidimensional GenAI usage, critical thinking disposition levels, and learning engagement behaviours.

Ultimately, an evaluation of associations among these variables was performed. Considering the descriptive-correlational nature of the study, Pearson product–moment correlation coefficients were used to examine the strength and direction of the relationships among GenAI usage, critical thinking, and learning engagement. Since the variables were computed as composite mean scores and the distributions met acceptable normality assumptions, Pearson correlation was considered appropriate. Jamovi software conducted all analytical procedures with a predefined significance threshold of $\alpha = 0.05$.

Ethical Considerations

All research was conducted in accordance with the rules of scholarly integrity and honesty. The data were collected, analysed, and presented without any interference in the acquisition of facts or biased selection. Any possible conflict of interest or ethical problem was disclosed according to the institution's rules and guidelines for research ethics. On March 24, 2026, ethical approval was obtained for the study, with protocol number: 2026-2nd-CASE-Zhao-v2.

All the subjects gave informed consent at first. The introduction page of the questionnaire was relatively clear about its objective, estimated completion time, range of data usage, confidential measures taken, as well as participants' rights to quit at will. Only those who had been invited to participate and had confirmed reading it voluntarily could access the official questionnaires.

The obligation to maintain confidentiality was also upheld. There was no personal data in the questionnaire; students' names, class numbers, and other details were not recorded. During the course of data analysis and summarisation, no specific personal information was revealed; thus, it is not available in this report.

Finally, the right to withdraw voluntarily was acknowledged. This activity is completely optional; there is no connection with the students' academic achievements, credits earned, and any assessment system. The respondents can end their participation in answering questions anytime without penalty.

RESULTS

Self-assessed usage of GenAI: frequency, contexts, purposes, methods

According to Figure 1, a large number of individuals have used GenAI tools repeatedly. The largest proportion of students (34.17%) used GenAI more than three times a day; another 23.89%, once or twice a day, making the total number of daily users reach 58.06%. Another 28.06% had interacted with GenAI more than once a week; therefore, 86.11% of all users were frequent visitors to the platform. Low-frequency or non-users represented only a small minority: 7.78% used GenAI weekly, and just 6.11% reported rare or no use at all. These findings indicate that AI tools have become embedded in students' daily academic practices.

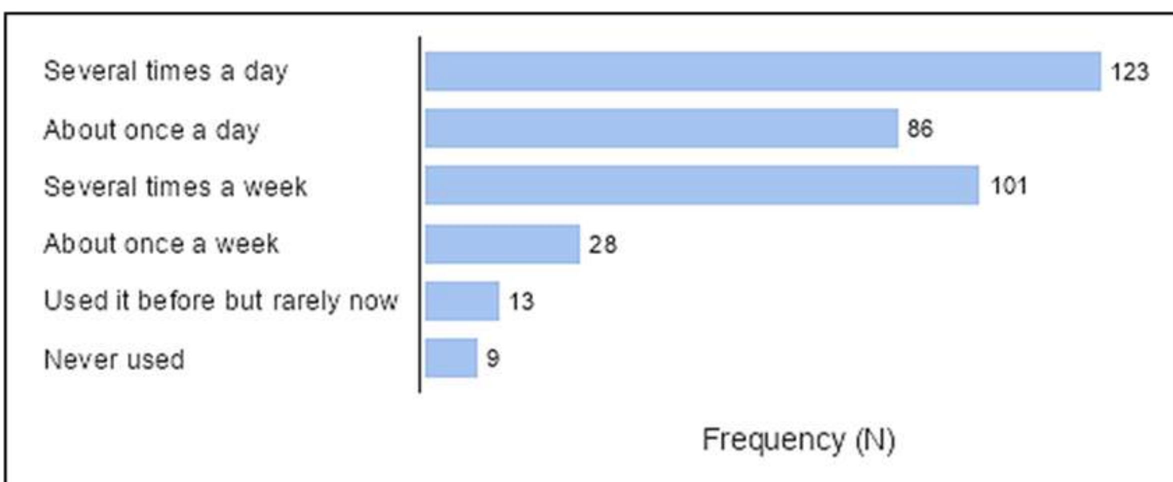

Figure 1. Summary of the Frequency of Usage of GenAI by the Respondents.
Source: Authors' own work

Table 2. Summary of the mean scores and descriptive interpretations of self-reported GenAI usage context, purpose, and methods.

Dimensions: GenAI Usage Behaviour	Mean	Interpretation	SD
Context	3.09	Slightly Low	1.33
Purpose	2.93	Slightly Low	1.31
Method	3.03	Slightly Low	1.31
Overall	2.99	Slightly Low	0.82

Source: Authors' own work. Scale interpretation: see the Instruments section.

As shown in Table 2, GenAI usage was characterised by relatively low scores across context (M = 3.09), purpose (M = 2.93), and method (M = 3.03). The overall mean (M = 2.99) indicates a slightly low level of structured or intentional use. Students mainly used GenAI for occasional academic support rather than as a central learning tool, and the method dimension further suggests a predominantly passive usage pattern, with limited prompt refinement, verification, or editing of AI outputs. Taken together, these findings indicate that students' GenAI usage was characterised by high frequency but low-depth engagement.

Critical Thinking Dispositions

As shown in Table 3, all dimensions of critical thinking dispositions were rated at a slightly low level (M = 3.03 overall). Among them, analytical skill scored highest (M = 3.14), while truth-seeking scored lowest (M = 2.89). Other dimensions—systematic skill (M = 2.95), cognitive maturity (M = 3.09), and inquisitiveness (M = 3.06)—also remained below the midpoint, indicating generally weak critical thinking dispositions across the sample. Overall, the results indicate a low and uneven profile of critical thinking dispositions, with no dimension reaching a high level.

Table 3. The summary of mean scores and descriptive interpretation of critical thinking.

Dimensions: Critical Thinking	Mean	Interpretation	SD
Truth Seeking	2.89	Slightly Low	1.01
Analytical skill	3.14	Slightly Low	0.83
Systematic skill	2.95	Slightly Low	0.62
Cognitive Maturity	3.09	Slightly Low	1.12
Inquisitiveness	3.06	Slightly Low	0.77
Overall	3.03	Slightly Low	0.87

Source: Authors' own work. Scale interpretation: see the Instruments section.

The correlation between GenAI usage and critical thinking

As presented in Table 4, GenAI usage did not relate to critical thinking in any uniform way. Frequency of use mattered little, but the quality of use—context, purpose, and method—produced divergent effects across the five thinking dimensions. Frequency offered no meaningful leverage. Small positive correlations appeared with analytical skill ($r = 0.195$, $p < 0.001$), systematic skill ($r = 0.157$, $p = 0.003$), and inquisitiveness ($r = 0.242$, $p < 0.001$), yet none exceeded 0.25. Truth-seeking ($r = -0.002$, $p = 0.974$) and cognitive maturity ($r = 0.013$, $p = 0.811$) showed no association at all. Merely increasing GenAI usage, then, was not associated with critical thinking.

Table 4. Test for assessing the correlation among GenAI usage and dimensions of critical thinking.

Critical Thinking		Use of Gen AI: Frequency	Context	Purpose	Method
Truth Seeking	Computed r	-0.002	-0.149	-0.161	-0.118
	p-value	0.974	0.005	0.002	0.025
Analytical skill	Computed r	0.195	0.705	0.685	0.64
	p-value	< .001	< .001	< .001	< .001
Systematic skill	Computed r	0.157	0.404	0.33	0.353
	p-value	0.003	< .001	< .001	< .001
Cognitive maturity	Computed r	0.013	-0.17	-0.246	-0.221
	p-value	0.811	0.001	< .001	< .001
Inquisitiveness	Computed r	0.242	0.65	0.619	0.608
	p-value	< .001	< .001	< .001	< .001

Source: Authors' own work. Scale interpretation: see the Instruments section.

By contrast, deliberate use correlated strongly with three dimensions. Analytical skill registered the highest coefficients: context ($r = 0.705$), purpose ($r = 0.685$), and method ($r = 0.640$), all $p < 0.001$. Systematic skill followed at a lower magnitude: context ($r = 0.404$), purpose ($r = 0.330$), and method ($r = 0.353$), all $p < 0.001$. Inquisitiveness fell between these two patterns: context ($r = 0.650$), purpose ($r = 0.619$), and method ($r = 0.608$), all $p < 0.001$. Structured, goal-oriented engagement with GenAI thus coincided with stronger analytic, systematic, and inquisitive thinking.

Yet this pattern inverted for truth-seeking and cognitive maturity. Context, purpose, and method each correlated negatively with truth-seeking ($r = -0.149$, $p = 0.005$; $r = -0.161$, $p = 0.002$; $r = -0.118$, $p = 0.025$) and with cognitive maturity ($r = -0.170$, $p = 0.001$; $r = -0.246$, $p < 0.001$; $r = -0.221$, $p < 0.001$). Frequency remained unrelated to both. A trade-off emerged: the very use patterns that sharpened analytic and inquisitive capacities coincided with diminished truth-seeking and cognitive maturity.

Quality of engagement, rather than quantity of use, shaped these outcomes. Purposeful, context-embedded, and methodologically critical use supported higher levels of analytical skill, systematic skill, and inquisitiveness. At the same time, the negative associations with truth-seeking and cognitive maturity suggest that more intentional GenAI use may also be accompanied by reduced tendencies toward independent verification and reflective judgment. These findings provide an important basis for the theoretical interpretation presented in the Discussion section.

Learning Engagement: Behavioural, cognitive and emotional engagement.

Table 5 presents students' Learning Engagement, which was generally weak; according to the six-point Likert Scale, all three dimensions were rated as "slightly low". Behavioural Engagement had a mean score of 3.10. Students had limited time to complete assignments; moreover, they were not proactive in class. They lacked interest in independent learning outside of the required curriculum work.

Table 5. Summary of the Mean Scores and Descriptive Interpretation on the level of learning engagement.

Dimensions: learning engagement	Mean	Interpretation	SD
Behavioural Engagement	3.1	Slightly Low	1.3
Cognitive Engagement	3.06	Slightly Low	1.27
Emotional Engagement	3.01	Slightly Low	1.33
Overall	3.06	Slightly Low	0.82

Source: Authors' own work. Scale interpretation: see the Instruments section.

Cognitive engagement was assessed as 3.06, ranking "slightly low"; Students reported limited use of deep-processing strategies such as critical analysis, thorough concept formation, knowledge synthesis, and self-reflection. Most relied on superficial memorisation without deep engagement with the underlying content. Emotional Engagement scores were the lowest, at 3.01. The academic motivation, enjoyment in learning, achievement emotion after difficulty resolution, and self-efficacy of the students were all relatively low. Scores show that students generally did not invest significantly in positive study habits.

The Relationship Between GenAI Usage and Learning Engagement

As illustrated in Table 6, GenAI usage related to learning engagement in a consistently positive pattern—unlike the mixed effects seen in critical thinking. Usage frequency demonstrated only weak positive correlations with the three learning engagement dimensions (Behavioural: $r = 0.263$; Cognitive: $r = 0.214$; Emotional: $r = 0.202$; all $p < 0.001$). These relatively modest coefficients suggest that merely increasing the frequency of

GenAI usage is associated with only limited improvements in students' behavioural participation, cognitive processing, and emotional investment in learning.

Table 6. Test of relationship between GenAI usage and learning engagement.

Learning Engagement		Use of GenAI: Frequency	Context	Purpose	Method
Behavioural Engagement	Computed r	0.263	0.64	0.705	0.686
	p-value	< .001	< .001	< .001	< .001
Cognitive Engagement	Computed r	0.214	0.666	0.696	0.692
	p-value	< .001	< .001	< .001	< .001
Emotional engagement	Computed r	0.202	0.69	0.747	0.714
	p-value	< .001	< .001	< .001	< .001

Source: Authors' own work. Scale interpretation: see the Instruments section.

In contrast, the Context, Purpose, and Method of GenAI usage exhibited strong positive correlations with all three dimensions of learning engagement. Purpose emerged as the strongest predictor across all dimensions, with particularly high coefficients for Behavioural Engagement, Cognitive Engagement, and Emotional Engagement— the highest correlation observed in the matrix. Context and Method also showed robust positive associations, indicating that integrating GenAI into academic contexts and employing critical methodological approaches are significantly linked to higher levels of student engagement.

Among the three engagement dimensions, Emotional Engagement displayed the strongest overall associations with intentional GenAI usage, suggesting that purposeful and structured interaction with GenAI tools is most closely related to students' emotional connection to learning, sense of achievement, and intrinsic motivation. Behavioural and Cognitive Engagement also showed strong positive relationships with Context, Purpose, and Method, though slightly lower in magnitude compared to Emotional Engagement.

The above findings demonstrate that the quality, rather than the quantity, of GenAI interaction is most strongly associated with enhanced learning engagement. Purposeful, context-embedded, and methodologically critical use of GenAI is linked to substantially higher levels of behavioural participation, cognitive investment, and especially emotional engagement.

DISCUSSION

The findings reveal that the educational implications of GenAI depend less on how frequently students use it than on how they engage with it. This pattern aligns with Gerlich's (2025) observation that students learn GenAI through trial and error rather than structured guidance.

Critical Thinking: A Trade-Off Pattern

The heterogeneous relationship between GenAI usage and critical thinking demands theoretical explanation. Quality of engagement (context, purpose, method) correlated positively with analytical skill, systematic skill, and inquisitiveness, but negatively with truth-seeking and cognitive maturity. This trade-off is not captured by binary frameworks that treat GenAI as uniformly beneficial or harmful.

Cognitive offloading theory (Gerlich, 2025; Abbas et al., 2024) helps explain the negative links. When students use GenAI methodically—crafting prompts, iterating outputs, verifying claims—they engage in distributed cognition that may strengthen analytical and systematic processing. Yet the same efficiency-oriented behaviours may reduce the disposition to independently seek truth or acknowledge complexity. Students grow adept at working with AI outputs while losing the habit of working against them—questioning assumptions, tolerating ambiguity, pursuing objective facts without external scaffolding. This interpretation is consistent with Larson et al.'s (2024) cyclical model of human-AI workflows: students in this sample may have mastered the generation and integration phases while neglecting verification.

The cultural context compounds this effect. Li (2003) noted that Chinese educational traditions emphasize respect for established knowledge and collective harmony. Students in this setting may use GenAI for meticulous cross-referencing of standard answers rather than disruptive inquiry, reinforcing a pattern where analytical skill improves (students can process more information efficiently) but truth-seeking atrophies (students lack the disposition to challenge or verify beyond the provided output).

Learning Engagement: Quality-Driven Uniformity

Unlike the mixed pattern in critical thinking, GenAI quality showed consistently positive associations with all three engagement dimensions. Purpose emerged as the strongest predictor, particularly for emotional engagement. Self-determination theory (Ryan & Deci, 2000) suggests that purposeful AI use satisfies competence needs—students feel effective when tools scaffold difficult tasks—while passive use undermines autonomy. The "effort paradox" documented by Haensch et al. (2023) may operate here: AI lowers initial barriers, but without clear goals, students lose the intrinsic motivation that sustains persistence. This finding suggests that purposeful AI use may promote engagement by supporting students' perceptions of competence and task relevance, consistent with self-determination theory.

Theoretical Contribution

These findings extend GenAI research in two ways. First, they suggest that quality-outcome relationships observed in elite institutions may also be present in resource-constrained regional universities, but with amplified trade-offs. Students in Henan

Province lack the institutional scaffolding—AI literacy workshops, clear policies, small-group instruction—that might mitigate cognitive offloading. Second, the results suggest that self-determination theory's autonomy-competence-relatedness framework may need revision to capture AI-mediated learning. When competence is outsourced to algorithms, the traditional link between competence satisfaction and intrinsic motivation may weaken.

Limitations

The cross-sectional design precludes causal claims. The Henan-only sample limits generalizability, and self-reported data may reflect social desirability bias. Longitudinal designs could track whether the observed trade-offs deepen or stabilize over time. Mixed-methods approaches combining surveys with behavioural observations would clarify whether students' self-reported "methodical" use matches actual verification behaviours. Instructional support and disciplinary differences warrant examination as moderators: STEM students may internalize verification routines differently from humanities students (Brachman et al., 2024).

CONCLUSIONS AND RECOMMENDATIONS

In conclusion, this study investigated GenAI usage patterns, critical thinking, and learning engagement among undergraduates at regional universities in Henan Province. The findings confirmed that students are frequent GenAI users, yet their engagement remains largely superficial—marked by passive use with limited integration into formal academic activities, clear learning objectives, or critical verification behaviours. Participants generally reported low levels of critical thinking across all five dimensions, with analytical skill showing the highest mean score and truth-seeking the lowest. Learning engagement was likewise generally low across the behavioural, cognitive, and emotional dimensions. Despite these overall low levels, the analysis demonstrated that the quality of GenAI engagement—specifically Context, Purpose, and Method—showed stronger positive associations with analytical skill, systematic skill, inquisitiveness, and all three dimensions of learning engagement than did usage frequency. However, these same intentional use dimensions were significantly negatively associated with truth-seeking and cognitive maturity, indicating a trade-off between stronger analytical and engagement-related outcomes and weaker epistemic dispositions, particularly truth-seeking and reflective judgment. These findings extend current understanding of how the quality of GenAI engagement, rather than usage frequency, is associated with different dimensions of critical thinking and learning engagement, while providing empirical support for integrating Critical Thinking Disposition Theory and Self-Determination Theory.

Based on these findings, several practical implications are proposed. Students should verify AI outputs against sources and define their own learning goals before using these tools, moving from passive copying to active questioning. For teachers, assignment design should be restructured so that students cannot complete tasks through AI alone by incorporating counter-argument generation, error identification in AI-generated texts, and open-ended problems requiring evaluation and synthesis. Teachers should also model critical AI use by demonstrating verification routines in class. Universities should integrate AI literacy into required courses, using concrete examples such as research methods and project-based assignments that fit the resources of regional institutions. Course loads and deadline clustering should be reviewed to reduce pressure for superficial AI use, and clear policies distinguishing legitimate AI-assisted learning from unacceptable substitution should be established to provide students with explicit guidance rather than ambiguous rules. These recommendations are aligned with international guidance on the responsible use of generative AI in higher education. UNESCO's Guidance for Generative AI in Education and Research emphasizes institution-wide AI literacy, transparent governance, ethical AI use, and the preservation of meaningful human agency in AI-supported teaching and learning (Holmes & Miao, 2023). Likewise, the Australian Framework for Artificial Intelligence in Higher Education highlights AI governance, AI literacy, assessment redesign, and staff capability as essential foundations for the responsible integration of generative AI into higher education (Lodge et al., 2025).

IMPLICATIONS

The findings of this study carry important implications for both research and practice. The results suggest that the effects of GenAI usage cannot be adequately interpreted through a simple "good or bad" dichotomy, as different dimensions of critical thinking are influenced in divergent ways. Self-determination theory's autonomy–competence–relatedness framework may require further refinement to better account for AI-mediated learning environments and the potential trade-offs they introduce in learner cognition and motivation. From a practical perspective, the findings indicate that educators may enhance student engagement through relatively simple interventions, such as encouraging students to set self-directed learning goals before using GenAI, which may improve motivational outcomes, while structured verification tasks and curriculum-integrated AI literacy training may help mitigate the risk of epistemic dependence and uncritical reliance on AI-generated outputs. At the policy level, the results suggest that investment in AI literacy should be extended to regional universities, where students demonstrate adoption levels comparable to those in elite institutions but often lack corresponding institutional support structures, and that policy frameworks should adopt more fine-grained evaluation criteria that promote the development of analytical skills without undermining truth-seeking and reflective judgment.

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DECLARATIONS

Conflict of Interest

The author declares no conflict of interest or financial ties to disclose. This manuscript is derived from the author's doctoral dissertation, which was independently conceived and developed. It has not been previously disseminated or published in any format, whether in books, online platforms, or scholarly journals.

Informed Consent

I hereby confirm my thorough review and complete understanding of the author guidelines set forth by this journal. I assert that my engagement in this publication is entirely voluntary, conducted with full knowledge and comprehensive information about its nature and all pertinent regulations.

Ethics Approval

This study was approved by the Institutional Ethics Review Committee of Trinity University of Asia (Protocol Code: 2026-2nd-CASE-Zhao-v2). All procedures were conducted in accordance with the ethical principles of respect, beneficence, and justice. The author affirms strict adherence to all ethical standards in conducting this research, thereby upholding the integrity and authenticity of its findings.

REFERENCES

Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education, 21*(1), Article 10. https://doi.org/10.1186/s41239-024-00485-4

Brachman, M., El-Ashry, A., Dugan, C., & Geyer, W. (2024, May). How knowledge workers use and want to use LLMs in an enterprise context. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems* (pp. 1–8). Association for Computing Machinery. https://doi.org/10.1145/3613905.3650841

Chan, M. M. K., Wong, I. S. F., Yau, S. Y., & Lam, V. S. F. (2023). Critical reflection on using ChatGPT in student learning: Benefits or potential risks? *Nurse Educator, 48*(6), E200–E201. https://doi.org/10.1097/NNE.0000000000001476

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... Wright, R. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Dwyer, C. P., Hogan, M. J., & Stewart, I. (2014). An integrated critical thinking framework for the 21st century. *Thinking Skills and Creativity, 12*, 43–52. https://doi.org/10.1016/j.tsc.2013.12.004

Facione, P. A. (1990). *Critical thinking: A statement of expert consensus for purposes of educational assessment and instruction (The Delphi Report).* California Academic Press.

Facione, P. A. (2000). The disposition toward critical thinking: Its character, measurement, and relationship to critical thinking skill. *Informal Logic, 20*(1). https://doi.org/10.22329/il.v20i1.2254

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

Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. *Societies, 15*(1), Article 6. https://doi.org/10.3390/soc15010006

Haensch, A. C., Ball, S., Herklotz, M., & Kreuter, F. (2023). Seeing ChatGPT through students' eyes: An analysis of TikTok data. In *2023 Big Data Meets Survey Science (BigSurv)* (pp. 1–8). IEEE. https://doi.org/10.1109/BigSurv57845.2023.10388979

Han, Y. Y. (2025). Cultivation of college students' critical thinking under the background of generative artificial intelligence: Values, challenges and strategies [In Chinese]. *Journal of Continuing Higher Education, 38*(3), 29–38.

Holmes, W., & Miao, F. (2023). *Guidance for generative AI in education and research.* UNESCO.

Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., ... Fung, P. (2023). Survey of hallucination in natural language generation. *ACM Computing Surveys, 55*(12), 1–38. https://doi.org/10.1145/3571730

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeiffer, F., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Koudela-Hamila, S., Santangelo, P. S., Ebner-Priemer, U. W., & Schlotz, W. (2022). Under which circumstances does academic workload lead to stress? *Journal of Psychophysiology.* Advance online publication. https://doi.org/10.1027/0269-8803/a000312

Larson, B. Z., Moser, C., Caza, A., Muehlfeld, K., & Colombo, L. A. (2024). Critical thinking in the age of generative AI. *Academy of Management Learning & Education, 23*(3), 373–378. https://doi.org/10.5465/amle.2023.0149

Li, J. (2003). US and Chinese cultural beliefs about learning. *Journal of Educational Psychology, 95*(2), 258–267. https://doi.org/10.1037/0022-0663.95.2.258

Lodge, J. M., Bower, M., Gulson, K., Henderson, M., Slade, C., & Southgate, E. (2025). *Australian framework for artificial intelligence in higher education.* Curtin University.

Retrieved July 27, 2026, from https://www.acses.edu.au/publication/australian-framework-for-artificial-intelligence-in-higher-education/

Niu, L., Behar-Horenstein, L. S., & Garvan, C. W. (2013). Do instructional interventions influence college students' critical thinking skills? A meta-analysis. *Educational Research Review, 9*, 114–128. https://doi.org/10.1016/j.edurev.2012.12.002

Peng, M. C., Wang, G. C., Chen, J. L., Chen, M. H., Bai, H. H., Li, S. G., Li, J. P., Cai, Y. F., Wang, J. Q., & Yin, L. (2004). Reliability and validity testing of the Chinese version of the California Critical Thinking Disposition Inventory [In Chinese]. *Chinese Journal of Nursing, 39*(9), 644–647.

Raman, R., Mandal, S., Das, P., Kaur, T., Sanjanasri, J. P., & Nedungadi, P. (2024). Exploring university students' adoption of ChatGPT using the diffusion of innovation theory and sentiment analysis with gender dimension. *Human Behaviour and Emerging Technologies, 2024*(1), Article 3085910. https://doi.org/10.1155/2024/3085910

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Sinatra, G. M., Heddy, B. C., & Lombardi, D. (2015). The challenges of defining and measuring student engagement in science. *Educational Psychologist, 50*(1), 1–13. https://doi.org/10.1080/00461520.2014.1002924

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

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