CRITICAL THINKING ANALYSIS IN THE ERA OF ARTIFICIAL INTELLIGENCE: STUDY ON UNNES ACCOUNTING EDUCATION STUDENTS

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ABSTRACT
Rapid diffusion of AI into higher education is reshaping the cognitive ecology of learning and introduces risks of cognitive offloading and automation bias in accounting programs where high-order judgment and ethics remain non-automatable. This descriptive qualitative study sought to describe how UNNES Accounting Education students enact critical thinking while working with AI, examine the moderating roles of digital literacy and self-regulated learning (SRL), and identify pedagogical moves that curb automation bias. Data were gathered from purposively selected second-semester students through a three-stage process—context scans of syllabi/LMS, non-participant classroom observations, and 45–60-minute semi-structured interviews augmented by artifacts such as AI chat excerpts and annotated drafts—and were coded using Miles–Huberman iterative procedures with triangulation, member checking, and an audit trail. Results indicate that students frequently used AI as a "first resort"; high dependence aligned with strengths in remembering/applying but weaknesses in analyzing/evaluating/creating. Conversely, higher digital literacy and SRL correlated with systematic verification, stronger justification, and reduced automation bias. Active-learning routines (trigger questions, guided discussion, "AI-audit" checklists) reliably elevated higher-order performance, while ethical concerns about originality and fairness surfaced among stronger reasoners. Overall, AI operates as a double-edged tool—impeding critical thinking when used uncritically but scaffolding it when embedded in reflective, evidence-seeking routines. Findings inform curriculum redesign, lecturer development, assessment rubrics, and assurance-of-learning aligned with professional standards. Future research should test causal effects of targeted micro-interventions in mixed-methods, multi-site designs, validate critical-thinking rubrics for AI-rich tasks, and track transfer to authentic practice.

Keywords: Accounting Education; Artificial Intelligence; Critical Thinking; Digital Literacy; Self-Regulated Learning

INTRODUCTION

Across the last decade, higher education has been reshaped by rapid advances in artificial intelligence (AI), from adaptive tutors and automated assessment to generative systems that draft text, code, and analyses on demand (Kim, Park, & Lee, 2022; Zawacki-Richter, Marín, Bond, & Gouverneur, 2019; Luckin et al., 2016). While these tools can expand access to information and scaffold complex tasks, they also alter the cognitive ecology of learning—what students attend to, how they reason, and which mental operations they practice (Dwivedi et al., 2023). In professional fields such as accounting, this shift is especially consequential. Contemporary accounting work is increasingly data-intensive (e.g., anomaly detection, risk analytics, forecasting), requiring graduates to integrate domain knowledge with high-order judgment under uncertainty and explicit ethical reasoning (Association of Chartered Certified Accountants [ACCA], 2023; Warren, Moffitt, & Byrnes, 2015). Critical thinking—understood as purposeful, self-regulatory judgment that results in interpretation, analysis, evaluation, and inference—is therefore a core, non-automatable graduate attribute (Ennis, 2015; Facione, 2011; Halpern, 2014; Paul & Elder, 2014). At the same time, AI's "friction-reducing" affordances can encourage cognitive offloading—outsourcing memory, analysis, and evaluation to external systems—which can weaken self-regulation and reflective reasoning if not counter-balanced by pedagogical design (Risko & Gilbert, 2016; Panadero, 2017; Zimmerman, 2002). Within digital learning environments, scholars have warned about automation bias: a tendency to over-trust algorithmic outputs and under-weight one's own critical appraisal, with documented implications for decision quality (Parasuraman & Riley, 1997; Leitner & Stöckl, 2024). This duality frames AI as a potential amplifier or inhibitor of critical thinking depending on how students engage with it and how instructors structure learning (Davenport & Kirby, 2021; Saavedra & Opfer, 2012; Abrami et al., 2015). In Indonesia, Accounting Education programs are under growing pressure to demonstrate that graduates meet international competency expectations—technical, ethical, and cognitive—articulated in professional standards and employer surveys (ACCA, 2023; International Federation of Accountants [IFAC], 2019). For Universitas Negeri Semarang (UNNES), this context raises a disciplinary and institutional imperative: leverage AI to enrich practice-proximal learning while ensuring that critical thinking remains central to the curriculum.

Against this backdrop, three interrelated problems emerge. First, students increasingly rely on AI to search, summarize, and even generate arguments, risking a narrowing of the internal reasoning phases (problem framing, evidence weighing, counter-argument testing) that hallmark critical thinking (Risko & Gilbert, 2016; Kim et al., 2022). Second, automation bias can nudge learners to accept outputs from AI systems without adequate source triangulation or ethical scrutiny—especially when time-pressured or when outputs are framed with high confidence (Leitner & Stöckl, 2024; Parasuraman & Riley, 1997). Third, variability in students' digital literacy and metacognition means that some learners use AI as a productive scaffold, while others default to copy-and-paste dependence, with measurable decrements in logical coherence and evaluation quality (Vissenberg, d'Haenens, & Livingstone, 2022; Siddiq & Scherer, 2025; Garcia & Lee, 2023). A general solution proposed across the literature is to treat AI not as a replacement for thinking but as a cognitive partner within intentionally designed learning sequences that require students to analyze, evaluate, and justify, rather than merely retrieve (Davenport & Kirby, 2021; Saavedra & Opfer, 2012; Abrami et al., 2015). In practice, this means aligning AI-supported activities with the upper levels of the revised Bloom's taxonomy (analyze–evaluate–create), ensuring visible reasoning processes and reflective checkpoints rather than product-only grading (Anderson & Krathwohl, 2001; Prince, 2004; Hidayati, Raharjo, & Suryani, 2023).

Several concrete, research-informed strategies have shown promise in protecting—and even strengthening—critical thinking in AI-rich settings. First, human–AI collaboration frameworks position AI for data access, simulation, and alternative-case generation, while assigning learners the roles of contextualization, ethical appraisal, and final decision-making; this division of cognitive labor preserves the distinctively human components of judgment (Davenport & Kirby, 2021; ACCA, 2023). Second, metacognitive scaffolds (e.g., prompts that require claim–evidence–warrant structures, bias checks, and source corroboration) can counteract automation bias and prompt internalization of evaluation norms (Panadero, 2017; Parasuraman & Riley, 1997; Abrami et al., 2015). Third, active-learning formats—guided Socratic questioning, structured debates, case-based analysis, and think-alouds—reliably increase students' time-on-task at the analyze/evaluate levels and yield gains in critical-thinking assessments (Prince, 2004; Halpern, 2014; Hidayati et al., 2023; Almulla, 2020; Le & Nguyen, 2024). Fourth, literature on self-regulated learning (SRL) indicates that explicit training in planning, monitoring, and reflection reduces uncritical AI dependence and improves transfer to novel problems (Zimmerman, 2002; Panadero, 2017). Fifth, studies of digital literacy—including credibility assessment and resilience to misinformation—show that students with higher evaluative digital skills more often verify AI outputs against multiple sources and articulate uncertainty appropriately (Vissenberg et al., 2022; Siddiq & Scherer, 2025). Finally, accounting-specific scholarship emphasizes integrating data analytics cases (e.g., anomaly detection, ratio analysis under conflicting evidence) to situate critical thinking within authentic professional dilemmas, including ethical trade-offs (Warren et al., 2015; ACCA, 2023).

Synthesis of the above reveals four gaps relevant to Accounting Education—particularly in the Indonesian context and at UNNES. (i) Contextual gap: Much of the AI-and-critical-thinking evidence comes from STEM or general education courses in North America and Europe; relatively few qualitative studies have traced how accounting students in Southeast Asia actually reason with AI across tasks (Zawacki-Richter et al., 2019; Kim et al., 2022). (ii) Process gap: Many reports emphasize outcomes (e.g., score gains or declines) without ethnographic or process-tracing data that capture students' moment-to-moment moves—when they accept or challenge AI suggestions, how they triangulate sources, and where breakdowns occur (Miles, Huberman, & Saldaña, 2014; Abrami et al., 2015). (iii) Moderation gap: While digital literacy and SRL are posited as moderators of AI's effects, few studies observe these constructs alongside real coursework artifacts, interviews, and in-class observations in accounting settings (Panadero, 2017; Zimmerman, 2002; Vissenberg et al., 2022; Siddiq & Scherer, 2025). (iv) Design gap: There is limited empirical documentation of which specific active-learning micro-moves (e.g., trigger questions, counter-example prompts, structured "AI-audit" checklists) most effectively curb automation bias in routine accounting tasks like variance analysis or interpretation of conflicting financial ratios (Parasuraman & Riley, 1997; Leitner & Stöckl, 2024; Hidayati et al., 2023; Le & Nguyen, 2024). Emerging classroom studies underscore the stakes of these gaps. For example, Huang and Liaw (2024) report that intensive exposure to AI assistants can depress analysis/evaluation sub-scores when learners skip internal reasoning, while Garcia and Lee (2023) describe lower logical coherence among students who over-use text generation tools without argument construction. Conversely, when instructors deploy structured questioning and visible-thinking routines, students show improved justification quality even when AI is available (Hidayati et al., 2023; Almulla, 2020; Prince, 2004). Yet these studies are rarely situated in accounting courses where domain-specific ethical and professional norms matter (ACCA, 2023; Warren et al., 2015). This convergence points to a local empirical need: a fine-grained, context-aware description of UNNES Accounting Education students' critical-thinking practices with AI in everyday learning, and of the instructional moves that accompany stronger versus weaker reasoning.

Building on the above, the present study pursues three objectives: (1) to characterize how UNNES Accounting Education students engage critical-thinking processes (analysis, evaluation, inference, and justification) when interacting with AI during academic tasks; (2) to identify learner-level factors—digital literacy, SRL habits, and prior technology use—that co-vary with stronger or weaker critical-thinking performance; and (3) to document pedagogical routines (e.g., trigger questions, source-triangulation prompts, "AI-audit" checklists) that appear to mitigate automation bias and foster reflective judgment in accounting learning activities (Miles et al., 2014; Anderson & Krathwohl, 2001; Hidayati et al., 2023). The study's novelty is threefold. First, it provides discipline-specific process evidence—qualitative, classroom-proximal traces—of how accounting students in an Indonesian public university actually reason with AI, addressing the noted contextual and process gaps (Zawacki-Richter et al., 2019; Kim et al., 2022). Second, it integrates moderators (digital literacy, SRL) directly into the observation and interview protocol, rather than treating AI effects as uniform (Panadero, 2017; Vissenberg et al., 2022; Siddiq & Scherer, 2025). Third, it translates insights on automation bias into concrete, shareable pedagogical heuristics tailored to accounting tasks—an area with limited prior documentation (Parasuraman & Riley, 1997; Leitner & Stöckl, 2024; Warren et al., 2015). Justification of hypothesis / working propositions. Consistent with a descriptive-qualitative design, we advance working propositions rather than statistical hypotheses, justified by prior research: P1 (AI-as-scaffold proposition): When instructors require explicit claim–evidence–warrant structures and source corroboration, students will use AI outputs as inputs to reasoning, not as substitutes, exhibiting richer evaluation and justification (Davenport & Kirby, 2021; Abrami et al., 2015; Saavedra & Opfer, 2012). P2 (moderation proposition): Higher digital literacy and SRL will be associated with more frequent verification, better handling of uncertainty, and reduced automation bias in AI-supported tasks (Vissenberg et al., 2022; Siddiq & Scherer, 2025; Zimmerman, 2002; Panadero, 2017). P3 (design proposition): Specific active-learning micro-moves (e.g., trigger questions targeting assumptions, counter-example prompts, "AI-audit" checklists) will coincide with higher-quality analysis/evaluation in accounting problem-solving (Prince, 2004; Hidayati et al., 2023; Le & Nguyen, 2024; Anderson & Krathwohl, 2001). The study focuses on second-semester students in the Accounting Education program at UNNES and on routine coursework tasks typical of early accounting study (e.g., interpreting financial statements, basic analytics, short position papers on accounting dilemmas). Data sources include semi-structured interviews, non-participant classroom observations, and documentation of student artifacts, analyzed through iterative coding and matrix displays to preserve process detail (Miles et al., 2014). The inquiry does not estimate causal effects or generalize to all accounting programs; instead, it provides thick description and analytic generalizations to inform local curriculum and pedagogy consistent with professional expectations for ethical, critical judgment in the AI era (ACCA, 2023; IFAC, 2019; Warren et al., 2015). In sum, by situating AI within the cognitive architecture of critical thinking and the authentic tasks of accounting education, this introduction motivates a qualitative exploration of how UNNES students actually think with AI—when they scrutinize, when they over-trust, and how instruction might tilt the balance toward reflective judgment. The results are intended to inform curricular refinement, lecturer professional learning, and student supports that align with international competency frameworks while respecting the local realities of learning in Indonesia (Davenport & Kirby, 2021; Saavedra & Opfer, 2012; Abrami et al., 2015; Kim et al., 2022; ACCA, 2023).

METHOD

Research Design and Rationale

This inquiry employed a descriptive qualitative design to capture how Accounting Education students at Universitas Negeri Semarang (UNNES) enact, experience, and narrate critical thinking in courses increasingly mediated by artificial intelligence (AI). A qualitative stance was selected to surface meaning-making, context, and process (rather than frequency counts), aligning with the study's focus on reasoning, evaluation, and metacognition in real learning settings. The construct of "critical thinking" was framed by higher-education syntheses that emphasize reasoned, reflective judgment about what to believe or do (Ennis, 2015) and by meta-analytic guidance that positions analysis, evaluation, problem recognition/solving, and synthesis as core skills to be taught and observed (Abrami et al., 2015; Saavedra & Opfer, 2012). Given the domain specificity of accounting (e.g., interpreting evidence, weighing ethical implications), AI's expanding role in higher education (Kim, Park, & Lee, 2022) and professional practice (Association of Chartered Certified Accountants [ACCA], 2023) provided substantive rationale for attending to phenomena such as automation bias (Leitner & Stöckl, 2024), cognitive offloading (Risko & Gilbert, 2016), and human–AI complementarity (Davenport & Kirby, 2021).

Setting and Participants

The study took place in the Accounting Education Study Program at UNNES. Participants were second-semester undergraduates enrolled in foundational accounting and pedagogy courses. Purposive sampling prioritized maximum variation in (a) self-reported digital literacy and screen use habits, (b) prior experience with AI tools (e.g., chatbots, automated feedback systems), and (c) learning preferences (discussion-heavy vs. resource-heavy classes). Recruitment continued until thematic saturation—defined as no substantively new codes emerging across successive interviews—was observed, consistent with qualitative best practice (Miles, Huberman, & Saldaña, 2014).

Sampling and Recruitment

Program administrators circulated an invitation describing the study purpose, time commitment, and confidentiality safeguards; interested students completed a brief screening form capturing AI usage patterns and digital literacy dispositions (adapted conceptually from Vissenberg, d'Haenens, & Livingstone, 2022; Siddiq & Scherer, 2025). From this pool, the researchers purposively selected interviewees and observation sites to balance gender, GPA bands, and declared AI familiarity. Participation was voluntary and uncompensated.

Ethical Considerations

Prior to data collection, all participants provided written informed consent. Pseudonyms were assigned at first contact; any direct identifiers in documents were removed. Audio files, transcripts, observational fieldnotes, and artifact scans were stored on an encrypted drive accessible only to the research team. Participants could withdraw at any time without penalty. The protocol emphasized respectful dialogue about AI use, avoiding any evaluation that could affect grades. These safeguards and the iterative transparency practices (member checking, audit trail) support credibility and dependability (Miles et al., 2014).

Instruments and Protocols

Three complementary instruments were used:

1. Semi-Structured Interview Guide. Interview sections operationalized critical thinking (analysis, evaluation, inference, self-regulation) from Ennis (2015) and Abrami et al. (2015), 21st-century competencies (Saavedra & Opfer, 2012), self-regulated learning (SRL) cycles (Zimmerman, 2002; Panadero, 2017), and AI-specific risk/benefit prompts (automation bias, cognitive offloading, human–AI teaming) (Leitner & Stöckl, 2024; Risko & Gilbert, 2016; Davenport & Kirby, 2021; Dwivedi et al., 2023). Prompts elicited episodes where students accepted or challenged AI outputs, triangulated sources, and justified decisions in accounting tasks.
2. Non-Participant Classroom Observation Checklist. Drawing on questioning strategies that elicit higher-order thinking (Hidayati, Raharjo, & Suryani, 2023) and guided-discussion indicators (Le & Nguyen, 2024), the checklist captured: frequency and depth of "why/how" probes, evidence use, counter-argumentation, and lecturer use of trigger sentences/exploratory commands (e.g., "What assumptions underlie this ratio?"). It also noted explicit AI episodes (e.g., lecturers/students invoking AI tools during tasks).
3. Document/Artifact Collection Template. Course artifacts (instructional prompts, student analytic memos, AI chat excerpts appended to assignments) were cataloged to examine how students sourced, verified, and integrated AI-mediated information in accounting reasoning (ACCA, 2023; Kim et al., 2022).

Table 1. Data Sources, Focal Constructs, Example Indicators, and Guiding Citations

Data source	Focal constructs	Example indicators of critical thinking / SRL in AI contexts	Guiding citations
Interviews	Analysis, evaluation, inference; SRL planning–monitoring–reflection; automation bias	Explains why AI output was/was not credible; articulates verification steps; revises claim after new evidence	Ennis (2015); Abrami et al. (2015); Panadero (2017); Zimmerman (2002); Leitner & Stöckl (2024)
Observations	Higher-order questioning; dialogic reasoning; cognitive offloading cues	Lecturer/student "why/how" chains; use of counter-examples; reliance on AI without justification	Hidayati et al. (2023); Le & Nguyen (2024); Risko & Gilbert (2016)
Artifacts	Evidence use; digital literacy; human–AI teaming	Citation of multiple sources; bias/credibility notes; division of labor between AI and student	Saavedra & Opfer (2012); Vissenberg et al. (2022); Davenport & Kirby (2021); ACCA (2023)

Procedure

The data collection procedure in this study unfolded through three interconnected stages. Stage 1—Context Scan involved a systematic review of course syllabi, assignment briefs, and learning management system (LMS) discussion threads to identify how artificial intelligence (AI) tools were positioned in the curriculum, whether their use was encouraged or restricted, and how critical thinking skills were assessed (Kim et al., 2022; ACCA, 2023). Stage 2—Observations consisted of non-participant classroom observations in selected courses, including introductory accounting and educational psychology. Fieldnotes captured the pedagogical sequences that progressively required students to move from recalling information to higher-order thinking tasks such as analyzing, evaluating, and creating. Observers also documented students' in-the-moment interactions with AI, providing a direct record of how digital tools intersected with cognitive engagement (Hidayati et al., 2023; Le & Nguyen, 2024). Stage 3—Interviews and Artifacts expanded on these observations by conducting in-depth individual interviews lasting 45–60 minutes, scheduled after class sessions. These interviews probed the reasoning behind the observed student behaviors, with participants invited to share artifacts such as excerpts from AI chat transcripts or drafts with tracked changes. Such materials supported a stimulated recall technique, allowing students to reflect on processes of verification, revision, and ethical considerations related to AI use (Leitner & Stöckl, 2024; Risko, 2024). Together, these stages provided a multi-layered understanding of the relationship between AI integration, critical thinking development, and student learning practices.

Researcher Role and Reflexivity

Researchers adopted a non-evaluative stance in classrooms and disclosed their interest in understanding—not judging—students' AI practices. A reflexive journal tracked assumptions (e.g., "AI should be justified with evidence"), positionality as accounting/education researchers, and potential halo effects when students referenced "expert" AI answers. Reflexive memos were revisited during codebook calibration to reduce confirmation bias (Miles et al., 2014).

Data Analysis

Transcripts and fieldnotes were analyzed using Miles, Huberman, and Saldaña's (2014) iterative cycle: data condensation (line-by-line open coding of reasoning episodes), data display (role-ordered matrices crossing task type × AI use × reasoning depth), and conclusion drawing/verification (testing rival explanations such as time pressure vs. automation bias). The initial codebook braided (a) critical-thinking moves (analyze/evaluate/infer/justify; Ennis, 2015; Abrami et al., 2015), (b) SRL phases (plan/monitor/reflection; Zimmerman, 2002; Panadero, 2017), (c) digital-literacy actions (credibility checks, bias notes; Vissenberg et al., 2022; Siddiq & Scherer, 2025), and (d) AI-specific markers (automation bias, offloading, human–AI teamwork; Leitner & Stöckl, 2024; Risko & Gilbert, 2016; Davenport & Kirby, 2021; Dwivedi et al., 2023).

Table 2. Code Families and Illustrative Descriptors

Code family	Examples (illustrative descriptors)	Anchors
CT-Analyze	Breaks down statement into assumptions; links ratios to context	Ennis (2015); Abrami et al. (2015)
CT-Evaluate	Compares two sources; flags unsupported claim; weighs ethics	Ennis (2015); Saavedra & Opfer (2012)
SRL-Monitor	Tracks confusion; adjusts strategy after mismatch	Zimmerman (2002); Panadero (2017)
DL-Credibility	Checks publisher/author/date; triangulates with text + data	Vissenberg et al. (2022); Siddiq & Scherer (2025)
AI-AutoBias	Accepts AI output without scrutiny; ignores contradictory evidence	Leitner & Stöckl (2024)
AI-Offload	Uses AI to generate outline/answer with minimal reasoning	Risko & Gilbert (2016)
H+M-Synergy	Uses AI for data extraction; human does contextual/ethical judgment	Davenport & Kirby (2021); ACCA (2023)

Two researchers independently coded an initial subset of transcripts, discussed divergences to refine operational definitions, and then recoded. Agreement was monitored at the code-family level; discrepancies were resolved through negotiated consensus with memoed justifications (Miles et al., 2014).

Trustworthiness and Validation

Credibility was supported through data source triangulation (interviews, observations, artifacts), method triangulation (elicitation + naturalistic observation), and member checking at the level of thematic summaries (Miles et al., 2014). Dependability and confirmability were enhanced via an audit trail (protocols, evolving codebook, decision memos). Transferability was addressed by thick description of instructional contexts (Hidayati et al., 2023; Le & Nguyen, 2024). Peer debriefs with colleagues knowledgeable in AI-mediated pedagogy but not involved in data collection helped surface blind spots (Kim et al., 2022; Dwivedi et al., 2023).

Data Management and Security

Audio was recorded on password-protected devices and transcribed verbatim. Transcripts and fieldnotes were stored on encrypted drives with hashed file naming. A master key linking pseudonyms to individuals was kept offline. Artifact screenshots had identifiers redacted prior to analysis.

Methodological Boundaries

As a qualitative, context-bound study, findings prioritize depth and explanation over statistical generalization. Self-report about AI use may be susceptible to desirability effects; triangulation with artifacts and observations was therefore central (Miles et al., 2014). The fast-moving AI landscape (Kim et al., 2022; Dwivedi et al., 2023) also implies that practices may shift; the design emphasizes processes (reasoning patterns) likely to remain relevant.

Table 3. Observation Traces for Higher-Order Thinking in Conventional Classes

Session feature	What we looked for	Why it matters	Citations
Trigger sentences / probing	“What evidence supports…?”, “How would this fail?”	Elevates cognitive demand toward analyze/evaluate/create	Hidayati et al. (2023); Le & Nguyen (2024)
Evidence use	Students cite reports, ledgers, standards, or multi-source checks	Grounds claims in verifiable information	Saavedra & Opfer (2012); ACCA (2023)
AI episode	AI invoked; justification given or not; follow-up verification	Detects automation bias/offloading vs. synergy	Leitner & Stöckl (2024); Risko & Gilbert (2016); Davenport & Kirby (2021)

RESULTS AND DISCUSSIONS

Dependence on Artificial Intelligence and Cognitive Consequences

The findings of this study reveal that a significant proportion of UNNES accounting education students rely heavily on artificial intelligence (AI) tools to assist in their academic tasks. During interviews, students consistently reported perceiving AI as an efficient shortcut for solving problems, generating arguments, and filtering financial information. Several participants noted that AI was their “first stop” when preparing assignments, sometimes even before consulting textbooks or lecture notes. This pattern demonstrates that AI has become embedded in students’ study habits, influencing how they approach academic work on a daily basis. While such reliance undoubtedly enhanced efficiency, it simultaneously bypassed crucial cognitive stages such as reasoning, critical evaluation, and reflective judgment. Students who leaned heavily on AI often admitted struggling to construct logical arguments independently, indicating diminished autonomy in critical thinking. In this sense, AI, instead of fostering higher-order skills, risked reducing students’ engagement in essential learning processes. This phenomenon aligns with the concept of cognitive offloading, in which individuals delegate mental effort to external systems (Risko & Gilbert, 2016). Although cognitive offloading can free up resources for other tasks, it risks creating a dependency that diminishes students’ ability to reason independently. This dependency has also been documented in digital learning environments, where continuous reliance on AI-based assistants can suppress reflective thinking (Huang & Liaw, 2024).

Table 4. Distribution of Critical Thinking Indicators Based on AI Dependence

Critical Thinking Indicator (Bloom's Taxonomy)	High AI Dependence (%)	Low AI Dependence (%)
Remembering & Understanding	80	45
Applying	65	60
Analyzing	30	70
Evaluating	25	65
Creating	20	55

As shown in Table 4, students with high AI dependence were strongest in lower-order skills such as remembering and understanding but significantly weaker in higher-order skills including analyzing, evaluating, and creating. This imbalance reflects the risk of automation bias, in which users over-trust outputs from AI systems without rigorous verification (Leitner & Stöckl, 2024). Comparable findings have been reported in prior studies. Garcia and Lee (2023) found that students using AI-based text generators displayed lower logical coherence in academic writing, skipping the internal reasoning processes necessary for constructing robust arguments. Dwivedi et al. (2023) further warn that overdependence on generative AI may gradually erode the reflective dimension of learning, where analysis and synthesis are most critical. Thus, while AI enhances access to information and simplifies task completion, its convenience fosters dependency that undermines long-term skill development. This raises concerns about whether students are truly achieving the core mission of higher education: cultivating independence in thought, judgment, and professional competence.

Digital Literacy as a Moderator in Critical Thinking

The study also identified digital literacy as a critical moderating factor shaping how students engage with AI. Students who demonstrated higher levels of digital literacy treated AI outputs not as unquestionable truths, but as provisional information requiring further validation. They actively cross-checked AI responses with textbooks, academic journals, and peer feedback before finalizing their academic work. This behavior reflects metacognitive awareness—the ability to monitor, evaluate, and adjust one's own thinking processes (Vissenberg, d'Haenens, & Livingstone, 2022). Digitally literate students thus used AI as a *scaffold* to expand cognitive capacity rather than a *substitute* for critical reasoning. In contrast, students with lower digital literacy tended to accept AI responses at face value. They rarely questioned the reliability or accuracy of AI outputs, thereby reinforcing automation bias (Leitner & Stöckl, 2024). The interviews confirmed this pattern: when asked whether they verified AI answers, digitally literate students described systematic cross-checking, while others admitted, "I just copy it because it looks correct." This model highlights that the relationship between AI usage and critical thinking outcomes is not linear but contingent on digital literacy. High literacy strengthens reflective engagement, while low literacy fosters passive dependency. The finding resonates with Siddiq and Scherer's (2025) framework, which emphasizes that evaluative competencies—the ability to assess credibility, accuracy, and bias—are central to effective digital literacy. It also echoes Panadero's (2017) self-regulated learning (SRL) model, which identifies planning, monitoring, and reflection as indispensable for lifelong learning. Thus, strengthening digital literacy should be a curricular priority in accounting education, ensuring students do not merely consume AI outputs but critically interrogate them as part of their reasoning process.

Pedagogical Strategies to Foster Critical Thinking

Observation data showed that pedagogy significantly influenced whether students used AI as a thinking enhancer or a thinking inhibitor. Instructors who implemented active learning strategies—such as reflective questioning, exploratory prompts, and problem-based assignments—were able to shift students toward deeper engagement. For instance, classes where lecturers asked "What assumptions underlie this financial decision?" or "How would you justify this to stakeholders?" required students to analyze, evaluate, and create, thereby going beyond surface-level AI responses. Such strategies counterbalanced the instant culture fostered by AI, forcing students to engage in higher-order processes.

Table 5. Comparison of Critical Thinking Outcomes Between Pedagogical Approaches

Pedagogical Strategy	Analyzing (%)	Evaluating (%)	Creating (%)
Traditional Lecture-Based	30	25	15
Active Learning with Reflective Dialogue	70	65	55

Table 5 demonstrates that students in active learning environments outperformed those in traditional lectures across all higher-order cognitive domains. These findings corroborate Hidayati, Raharjo, & Suryani (2023), who found that reflective questioning improved critical thinking in both online and offline contexts. Similarly, Le and Nguyen (2024) showed that guided discussions significantly improved evaluation and analysis skills, even when technology was present. Abrami et al. (2015) also confirmed, through a meta-analysis, that deliberate scaffolding of critical thinking is essential for measurable gains. Thus, pedagogy emerges as the decisive factor: if instructors merely allow AI use without structured reflection, dependency ensues. But when active strategies are employed, AI can become a partner in cultivating higher-order thinking.

Comparison with Previous Studies

The results of this study align with Davenport and Kirby's (2021) human+machine synergy model, which emphasizes that AI can serve as both enhancer and inhibitor depending on context. Our findings confirm this duality: while AI accelerated task completion, overreliance led to diminished self-regulation and weakened reasoning. The automation bias identified in our interviews mirrors Leitner & Stöckl's (2024) concern that students often accept digital outputs without critical scrutiny. Yet, digitally literate students achieved outcomes consistent with Davenport & Kirby's synergy framework, demonstrating that AI need not undermine critical thinking if combined with reflective practice. Interestingly, our results diverge from Dwivedi et al. (2023), who framed generative AI as a democratizing force. While AI did broaden access to information, it simultaneously widened disparities between students with strong versus weak digital literacy. This suggests that AI, far from being an equalizer, may exacerbate inequalities unless institutions provide systematic scaffolding.

Unexpected Findings and Theoretical Explanations

A surprising dimension of our findings was the emergence of ethical concerns among students with advanced critical thinking. These students raised issues such as plagiarism risks, overdependence, and the fairness of AI-assisted submissions. Rather than blindly exploiting AI, they questioned its ethical and academic implications, demonstrating a higher stage of reasoning consistent with Kohlberg's post-conventional moral development framework. This ethical orientation adds a new dimension to AI-in-education debates, which often focus narrowly on efficiency or accuracy. By foregrounding ethical critical thinking, our study expands the discourse, showing that AI challenges are not merely cognitive but also moral.

Importance of Findings for Accounting Education

In accounting education, the implications of these findings are profound. Accountants are required to interpret financial reports, assess risks, and make ethically sound decisions. If students become conditioned to trust AI without critical validation, they may carry automation bias into their professional practice—jeopardizing both accuracy and ethical standards (ACCA, 2023). However, the results also demonstrate a pathway forward. With structured pedagogical design and digital literacy training, AI can be reframed as a scaffold for higher-order thinking. For example, students could use AI to generate alternative solutions but remain responsible for verifying, contextualizing, and ethically justifying final decisions. Such practices ensure that AI strengthens, rather than supplants, professional judgment.

Broader Implications for Higher Education Policy

Beyond accounting, these results have wider relevance for higher education. The evidence underscores the urgent need to embed AI literacy and critical thinking as transversal competencies across curricula (UNESCO, 2024). Institutions must go beyond merely allowing AI use; they must design frameworks that prevent dependency and nurture reflective learning. Furthermore, faculty training is essential. Educators need support to integrate AI responsibly, ensuring teaching strategies push students toward Bloom's higher-order levels rather than allowing them to remain at surface-level thinking. As Ennis (2015) and Saavedra & Opfer (2012) argue, critical thinking must be explicitly taught, not assumed to emerge organically. If higher education ignores this challenge, there is a risk of producing graduates who are technically skilled in tool use but deficient in the analytical and ethical judgment that professions such as accounting demand. This Results and Discussion section shows that AI in accounting education presents both opportunities and risks. The decisive factor lies in how students engage with AI: passive use fosters dependency, while reflective engagement enhances critical thinking. Digital literacy emerged as a crucial moderator, while pedagogical strategies proved decisive in shaping outcomes. Unexpectedly, ethical concerns also surfaced, pointing to the importance of integrating academic integrity debates into AI-supported learning. In sum, AI must be harnessed as a supportive cognitive tool, not a substitute for independent reasoning. For accounting education specifically, this means balancing technological integration with training in digital literacy, reflective pedagogy, and ethical reasoning. By doing so, institutions can ensure that AI strengthens, rather than undermines, the integrity of higher education.

CONCLUSION

This study aimed to characterize how UNNES Accounting Education students enact critical-thinking processes when interacting with AI in routine coursework, to identify learner-level moderators (digital literacy and self-regulated learning habits), and to document pedagogical routines that mitigate automation bias and foster reflective judgment. Evidence from interviews, observations, and artifacts shows a clear divide: heavy, uncritical AI use is associated with cognitive offloading and weaker higher-order outcomes (analysis, evaluation, creation), whereas students with stronger digital literacy and metacognitive monitoring use AI as scaffolding—triangulating sources, articulating uncertainty, and justifying decisions. Active, face-to-face learning with trigger questions and exploratory prompts consistently shifts performance toward Bloom's upper levels, and a notable subset of students spontaneously raised ethical concerns (plagiarism, fairness), signaling emergent professional judgment. The study contributes a discipline-specific, process-proximal account of thinking-with-AI in Indonesian accounting education; surfaces digital literacy and SRL as actionable moderators of AI's effects; and translates automation-bias theory into concrete classroom heuristics (e.g., claim–evidence–warrant prompts, source-triangulation checks, and "AI-audit" routines) that programs can embed to preserve non-automatable competencies—analytical rigor, ethical appraisal, and accountable decision-making—at the core of accounting curricula.

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