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AI-Driven Learning Tools and Gender Equity: Rethinking Inclusive Digital Pedagogies in Higher Education

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Abstract. The effect of AI empowerment was further explored regarding academic performance, digital interaction, and gender equity in the tertiary education sector. Through an explanatory sequential mixed-method research design, 210 undergraduate students and six faculty members of a Philippine state university were engaged in the study. Quantitative data came from pre- /post-test results, a digital engagement survey, and an emerging Gender-Inclusive Pedagogy Perception Scale (GIPPS) scale; qualitative data include the focus group interviews with students, follow-up interviews with faculty, and classroom observations. The results indicated that the learning gain of students who were instructed with AI-integrated knowledge was statistically higher ($M = 5.40$) than that of students in traditional instruction lessons ($M = 2.10$), $d = 1.06$, which had a large effect size. AI users also indicated significantly more digital engagement, $t(208) = 5.02$, $p < 001$, $d = .70$, as well as more positive views of gender-inclusive pedagogy, $t(208) = 3.41$, $p = 001$, $d = 0.47$. A one-way ANOVA was significant for gender identity on GIPPS scores, $F(2, 207) = 4.15$, $p = 017$, $\eta^2 = .04$, and the highest perceived inclusivity came from LGBTQ+ students. Qualitative findings indicated that AI was perceived as a non-judgmental feedback partner, that consistent AI responses may diminish gendered expectations, and that AI-mediated lifelong feedback can bolster learning confidence with faculty mediation. Findings were used to design an Inclusive AI Pedagogy Framework grounded in Social Cognitive Theory, Gender Schema Theory, and Feminist Pedagogy. Results add to evidence that AI-infused tools can hold promise for learning success and fostering gender-responsive and inclusive DLEs when used with critical teacher mediation and equity-sensitive design.

Keywords: Artificial Intelligence in Education; Digital Engagement; Gender Equity; Higher Education; Inclusive Pedagogy

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1. Introduction

Artificial intelligence (AI) has become central to contemporary higher education, shaping and deploying teaching, learning, and assessment. AI-supported learning environments increasingly offer automated feedback, adaptive learning pathways, and scalable instructional support that could push the boundaries of personalisation in large university classes (Chen et al., 2020; Holmes et al., 2021). In most HEI settings, AI technologies have been linked to increased grades and boosted efficiencies in teaching practices, especially when the feedback received is timely, task-related, and matched with learning goals (Bond et al., 2021; Zawacki-Richter et al., 2019). Such advances reflect the fact that AI is no longer in the background, but a space for learning that influences what students do, how they interact, and perceive themselves as learners over time. Meanwhile, the efficacy of AI tools is contingent on how they are integrated into pedagogy; teachers supporting students in their use of AI and administering ethical and equitable usage (Crompton & Burke, 2023).

While AI may benefit instruction efficiency and learning advancement, researchers warn that AI is not socially neutral and can perpetuate or exacerbate the inequalities if implemented without protective measures. Bias may arise when training data mirror past patterns of inequality, when systems are engineered with too few perspectives in mind, and when outputs are presumed authoritative rather than contestable (Bender et al., 2021; Ferrara, 2024; Hall & Ellis, 2023). In educational environments, biased feedback or analytics could impact how learners experience fairness, inclusion, and psychological safety that may disproportionately affect women and gender diverse students (UNESCO, 2023; Wang & Young, 2022).

Moreover, empirical work also suggests that women and marginalised learners may encounter extra challenges to adopting AI, such as a lack of access to supportive infrastructure, limited support from the institutions, and increased privacy-related issues with respect to surveillance, autonomy, or misrepresentation (Kalim et al., 2025; Møgelvang et al., 2024; Stöhr et al., 2024). These are not trivial concerns in higher education, where instructional technology doesn't just deliver content but influences classroom power dynamics, norms of participation, and students' sense of belonging.

There is an evident research void in this area, as the use of AI has boomed in higher education. While many AI research studies investigate learning outcomes, others concentrate on technology adoption and attitudes; however, few explore how AI is associated with (1) learning performance, (2) digital engagement, and (3) promoting gender-inclusive pedagogy. Yet even less disaggregate by gender identities the differences and explain the mechanisms with reference to existing learning theories that account for gender (Granström & Oppi, 2025; Holmes et al., 2022; Ma et al., 2024). Consequently, institutions have very little evidence-based guidance on whether AI can aid in achieving equity goals rather than focusing solely on efficiency. This knowledge gap is of particular significance in settings where gender stereotypes and inequitable participation continue, like many higher education (HE) institutions within the Philippines, where gender mainstreaming has been institutionalised as a national priority and inclusive digital learning becomes increasingly associated with SDG 4 (Quality Education) and SDG 5 (Gender Equality).

This research gap will be filled by looking into how AI-facilitated instruction is associated with student outcomes, digital engagement, and perceptions about gender-inclusive pedagogy among higher education students in the Philippines. The analysis is grounded in three intersecting theoretical perspectives. First, Social Cognitive Theory describes how self-efficacy is formed by mastery experiences, feedback, and the cyclical relations among personal beliefs, behaviour engagement, and the environment (Bandura, 1997; Schunk & DiBenedetto, 2020). Second, the Gender Schema Theory describes how learners perceive competence and participation in relation to internalised gendered norms that may be upheld or challenged by learning cues such as feedback and representation (Bem, 1981; Manasi et al., 2022).

Third, there is a focus on shared power and voice, reflexivity, and the critical interrogation of the production of knowledge in Feminist Pedagogy, which becomes particularly important when outputs may contain algorithmic bias (hooks 2020; Samarakoon 2025). Together, these lenses enable the present study to investigate not only whether AI contributes to improved outcomes but also how and for whom AI may facilitate inclusive education. While AI could support the scaling and effectiveness of inclusive digital learning, limited empirical research has been conducted on the outcomes of AI-enabled tools regarding uptake, engagement, and gender equity. Far fewer studies try to unpack these effects across different gender identities, or explore what's going on through integrated psychological, sociocultural, and feminist lenses. This divide limits universities' ability to 'optimise' the design of AI embeddings in a way that maximises academic achievement while also supporting gender-responsive inclusion.

1.1 Significance of the Study

This research is important as it addresses pressing global and local priorities in higher education, particularly social inclusion, equity, and gender-sensitive learning environments amid the rapid proliferation of AI. Through the integration of AI-based instruction with Social Cognitive Theory, Gender Schema Theory, and Feminist Pedagogy, this study contributes theory-driven evidence about how AI-mediated feedback may influence self-efficacy, inclusion, and gendered involvement. The results offer implications for educators by determining pedagogical situations in which AI can be used to assist learners without perpetuating harm, emphasising the significance of critical teacher-mediated and bias-aware learning designs.

The study also adds to evidence-based policymaking by providing a framework grounded in empirical research, in line with efforts on gender mainstreaming and equity-focused governance. At an academic level, the study seeks to redress a gap in research by combining gender-inclusive attitudes within one's perceptions of inclusivity, via learning outcomes and engagement, in a mixed-method approach, and by disentangling inclusivity perceptions across gender.

1.2 Research Problem

While the introduction of AI tools into higher education has been building, empirical research on the relationship between these technologies and learning outcomes, digital engagement, and gender in university classrooms remains scarce. Although AI-enabled personalisation with instantaneous feedback can add value, algorithmic bias, differences in gender experiences, and unequal levels of digital literacy remain challenges for students as well as teachers. In addition, we know little about how AI-driven feedback influences self-efficacy and internalises or resists gender schemas, and to what extent it aligns with feminist, gender-responsive pedagogy. This gap highlights the need for mixed-methods evidence and theory-driven frameworks to govern equitable, inclusive, and responsible AI use in higher education.

1.3 Research Questions

In what ways does AI-based instruction enhance students' learning performance and digital engagement compared to conventional instruction?
How do students perceive gender-inclusive pedagogy in AI-supported and traditional settings, by gender identity?
What do students and teachers say about AI-mediated learning in relation to inclusivity, fairness, confidence, or self-efficacy in learning?
How could combined quantitative and qualitative disclosure illuminate an inclusive AI Pedagogy Framework based on Social Cognitive Theory, Gender Schema Theory, and Feminist Pedagogy?

1.4 Literature Review

The literature in this paper covers previous work on AI in higher education, digital engagement, and gender and algorithmic bias, as well as the theoretical underpinnings that shape the scope of this study. The intention is to clear the ground regarding what is known and not known, and locate this study in relation to relevant empirical and theoretical debates. In IJLTER-style writing, the review of literature does not merely enumerate; it synthesises, savages, harmonises, and shows how the scholarship drives us to ask what we are asking.

1.4.1 AI in Higher Education: Learning Outcomes and Instructional Roles

According to systematic reviews, AI applications in higher education typically include automated feedback systems, intelligent tutoring systems, predictive analytics, and adaptive learning engines (Zawacki-Richter et al., 2019). Emerging evidence even indicates that AI is promising for improving learning by delivering just-in-time feedback, assisting self-regulated practices, and scaling personalised instruction up to the classroom level in a time- and cost-efficient manner (Chen et al., 2020; Jin et al., 2023). When used strategically, AI tools can help reduce both learners' and teachers' cognitive load for these everyday tasks, freeing up class time for deeper discussion and applied activities (Holmes et al., 2022). However, there is evidence suggesting that the readiness of institutions and ethical oversight may lag behind their rapid implementation (Bond et al., 2021; Crompton & Burke, 2023), possibly restricting long-term benefits for learning and creating inequalities in the experience of diverse groups of learners. Hence, AI in the University sector cannot simply be seen as a technological intervention but rather as a pedagogical technique deeply conditioned by governance, infrastructure, and classroom activities.

1.4.2 AI-Driven Learning Tools and Digital Engagement
AI-enabled learning tools have been associated with changes in digital engagement, but the effect may vary widely depending on the context and application. Luo et al. (2025) aggregated 63 empirical reports and reported that AI tools primarily promote assessment and evaluation, personalised feedback, and intelligent tutoring. The former two domains tend to have positive cognitive/affective outcomes. Of particular note in their study was the contradictory evidence regarding higher-order skills and critical thinking instruction. This ultimately indicates that better higher-order thinking connections are more likely to be associated with the quality of the design of an AI tool itself, rather than simply being present or absent.

Additional studies suggest that AI can increase engagement by fostering perceptions of care and presence. For example, chatbots provide an on-demand assistant that helps with explanations, practice, and feedback (Essel et al., 2022). Similarly, Jin et al. (2023) showed that AI applications did scaffold SRL in planning, monitoring, and reflection, all of which are intertwined with persistence and academic achievement. Nevertheless, research has tended to concentrate on the level of AI adoption rather than its quality of use. Infrequently do they inquire into the extent to which AI use mediates participation norms, unequal power relations, or inclusivity in the classroom (Granström & Oppi, 2025; Ma et al., 2024). These limitations highlight the importance of conceptualising engagement within context, not just as time on task, but as the multifaceted interplay of behavioural, cognitive, and motivational engagements with learning.

1.4.3 Gender Bias, Algorithmic Inequality, and Educational Risks
There is increasing evidence that AI systems can reflect bias, including gender bias, in data sources, modelling approaches, and deployment procedures. Tatman (2020) showed gender and dialect bias in automated captioning, demonstrating how performance differences can track with identity markers. Bender et al. (2021) also cautioned that large language systems may encode stereotypes and generate "fluent" outputs that are misleading (though pernicious if treated as neutral), contributing to perception-shaping and unjustified assumptions. Ferrara (2024) distilled sources of biases and bias impacts in AI systems, where biased training data and opaque governance could lead to discriminatory results.

In education, such issues can be important because feedback, analytics, or even recommendations could, in turn, influence evaluation, vetting, and access to opportunities, including how students interpret their own ability and belonging (UNESCO 2023; Wang & Young 2022). Beyond the technical aspect, gendered inequities can also be seen in accessing and feeling confident in using AI. For women and gender-diverse learners, there may be an increased relative level of caution in the use of AI or additional obstacles to adoption (Kalim et al., 2025;

Møgelvang et al., 2024; Stöhr et al., 2024). These trends suggest that equity in AI-mediated learning is conditioned by both design and context.

1.4.4 Theoretical Foundations and Integrative Logic

This study draws on three theoretical approaches to explain how AI can shape learning and gender-inclusive pedagogy.

Social Cognitive Theory: Social Cognitive Theory focuses on reciprocal determinism among the environment, behaviour, and personal factors, with the construct of self-efficacy as a critical mechanism that influences motivation, perseverance (persistence), and performance (Bandura, 1997). AI programs may serve as environmental affordances, providing repeated feedback and practice opportunities to develop mastery experiences and reduce anxiety (Lee et al., 2022). Timely, specific feedback can foster students' feelings of competence and resilience to persist in the face of challenges, increase their level of engagement, and result in better learning overall (Schunk & DiBenedetto, 2020). (The theory, however, warns that uncritical use of AI could weaken self-regulation if students come to outsource cognitive effort, possibly leading to shallow learning or a kind of digital dependency (Jo, 2024). Thus, the AI/self-efficacy association is dependent on pedagogical framing and support.

Gender Schema Theory: According to Gender Schema Theory (Bem, 1981), people view their experiences through the lens of gender expectations they have internalised, which determine what they expect and feel comfortable with in terms of competence, participation, and role prescriptions. However, feedback provided by AI may serve as a salient learning cue that strengthens or attenuates these schemas. When AI outputs reinforce stereotypes, they can further support expectations and exclusion based on gender, in contexts where gendered norms already serve as barriers to participation. In contrast, equitable and de-identified feedback may reduce the presence of bias cues that signal stereotype threat, leading to fairer participation and confidence (Cheryan et al., 2019; Manasi et al., 2022). Thus, promoting gender-inclusive outcomes requires attention to both AI products and classroom interpretation practices.

Feminist Pedagogy: Feminist pedagogy prioritises shared power, voice, reflexivity, and critical self-reflection on whose knowledge is valued (hooks, 2020). In the context of AI-assisted learning, feminist pedagogy argues that the authority of AI as a neutral and foregone entity should not go unchallenged. Instead, educators and learners need to mediate AI critically—analysing outputs, questioning biased rationales (there is none), and leveraging these tools for reflexive discussion about representation, fairness, and power (Kumar & Choudhury, 2022; Samarakoon, 2025). This is not a trivial perspective, since AI resources can subtly mediate classroom discussion by valorising particular modes of language use, knowledge, or assumptions.

Integrative Logic: AI Feedback in our model can also act as a self-efficacy enhancer (via Social Cognitive Theory), leading to increased engagement and performance. Concurrently, if AI feedback is considered to be neutral and constant, it may challenge gender schemas (Gender Schema Theory), leading to increased levels of perceived inclusiveness at least in the case of female and LGBTQ+ students. These pathways are reinforced or mediated by teacher and classroom power dynamics (Feminist Pedagogy), thereby shaping whether AI use will contribute to inclusivity and reflection or reproduce unseen biases. This holistic perspective directs the study's inquiry into outcomes, engagement, perceived inclusivity, and lived experiences.

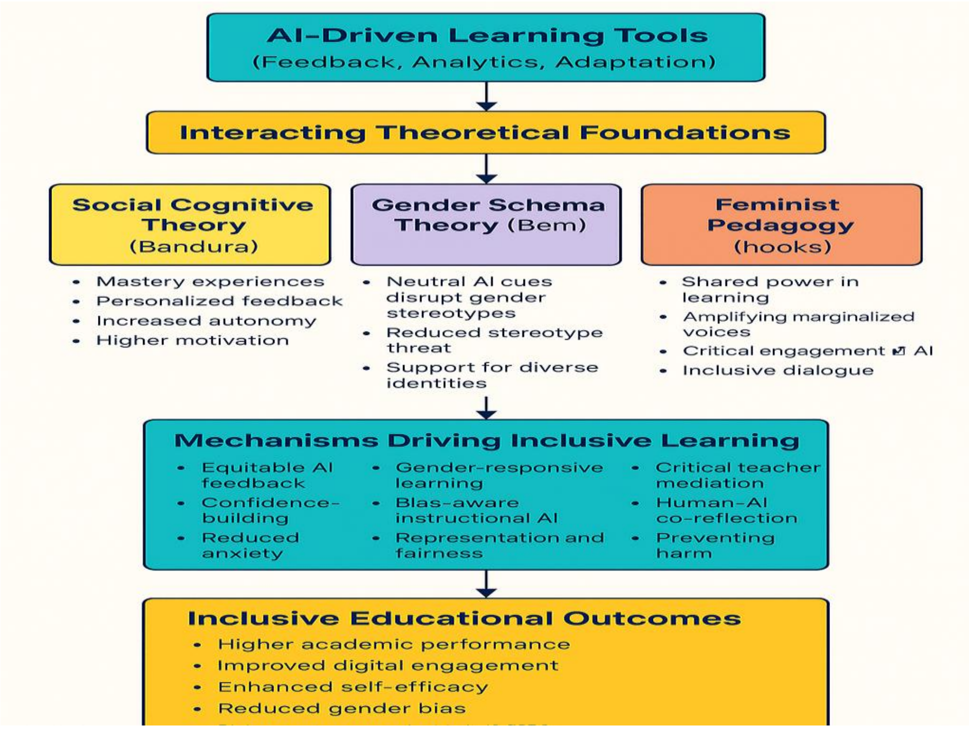

Figure 1: Theoretical Framework of the Study

2. Methodology

2.1 Research Design

A sequential explanatory mixed-methods design was used in this study. The objective of the quantitative phase was to determine whether AI-embedded pedagogy was associated with improved learning gains, greater digital engagement, and more positive attitudes toward gender-inclusive pedagogies. Next, in the qualitative phase, we interviewed students and faculty to understand how they perceived AI-based teaching in terms of fairness, inclusion, and confidence, which mediated the quantitative findings. The findings were then integrated into joint displays and through a theory-led synthesis; an Inclusive AI Pedagogy Framework, based on Social Cognitive Theory, Gender Schema Theory, and Feminist pedagogies, was developed. We opted for this design to enable statistical results to be grounded in participants' lived experiences and classroom practice, an essential requirement for investigating inclusion and equity within digitally mediated learning contexts.

2.2 Participants, Setting, and Sampling
A total of two hundred ten (210) students from a state university in the Philippines participated, along with six faculty members who handled subjects within the scope of investigation. To implement a 4-week intervention, the university utilised blended learning that combines AI-based teaching tools in course learning modules. For students' gender identification, we allowed respondents to self-select as males (n = 82), females (n = 105), or LGBTQ+ (n = 23) so that we could explore attitudes about inclusivity among these varied groups. Faculty participants (n = 6) were valuable contributors to our interview data and, as a result, their classroom observations provided insight into AI integration practices, bias-checking processes, and inclusive pedagogical techniques.

We adopted cluster sampling to select classes that had already been participating in blended learning. Two similar classes were matched for course type, program experience, and assessment format. Two classes were assigned to receive this intervention, namely the AI-integrated instructional condition (n = 110), and two other classes received traditional instruction (n = 100). All students in these classes were offered the opportunity to participate, remaining voluntary with informed consent. Cluster sampling was chosen because it preserved naturally occurring classroom clusters and reduced contamination between instructional conditions. Intact classes were assigned, and this may have introduced potential contextual differences; however, these comparability issues were controlled by the fact that courses had similar structures, and outcome measures were standardised.

2.3 Instruments and Quality Procedures
To meet reviewers' needs, we provide descriptions of instruments by type, format, number of items, utility, and psychometric characteristics.

2.3.1 Learning Performance Test (30 items)
A 30-item multiple-choice test developed by one of the researchers was used to assess achievement of course-aligned learning outcomes. Administered as a pre-test and post-test, the test made it possible the calculate gain scores. Items were created based on a blueprinting process of matching learning expectations and content, congruent with course objectives and instruction coverage. Item relevance, clarity, and congruence were confirmed by expert review of subject specialists on the content validity. The development of item wording and the distribution of item difficulty were refined based on pilot testing. Reliability: The internal consistency of the test was acceptable; KR-20 =. 89.

2.3.2 Digital Engagement Scale (24 items)
Digital engagement was measured using a 24-item Likert-scale questionnaire based on three dimensions: behavioural engagement (e.g., participation and completion behaviours), cognitive engagement (e.g., deep processing, strategic use), and motivational engagement (e.g., interest, persistence). Content Items were derived from established engagement constructs and subjected to expert validation for context-specific relevance. The feedback from the pilot was used to improve item clarity and reduce ambiguity. Internal consistency reliability was strong (Cronbach's α =. 91.

2.3.3 Gender-Inclusive Pedagogy Perception Scale – GIPPS (20 items)
GIPPS is a 20-item (Likert-type) instrument developed to assess perceived gender inclusivity in AI-supported learning. It assesses perceptions of fairness in feedback, psychological safety, representation and voice, and participation, and respect for gender diversity in classroom interactions. Developmental procedures involved (a) erecting the construct of inclusive pedagogy from literature in inclusive and feminist pedagogies, (b) constructing an item pool, (c) expert review for relevance and cross-cultural appropriateness of items, and (d) pilot testing with item refinement. The internal consistency reliability was satisfactory with a Cronbach's α of 88.

2.3.4 Qualitative Tools
Qualitative data, on the other hand, were gathered through (a) a focus group discussion guide, (b) a faculty interview guide, and(c) a classroom observation checklist. These instruments were developed to record experiences with AI-generated feedback, perceptions of inclusivity and fairness, gendered interaction patterns, and teachers' mediating practices. To establish trustworthiness, data were triangulated across student focus group discussions, faculty interviews, and classroom observations. An audit trail was established through coding memos and analytic decisions, and peer debriefing enhanced the themes.

2.4 Quantitative Data Collection Procedures
All participants (both HG and CG) underwent a learning pre-test before the intervention to control for baseline performance. The AI-enhanced group had access to AI-integrated tools in the learning modules for 4 weeks. These tools were guided by AI feedback on practice tasks, formative checks, and reflective questions. In contrast, the control cohort followed traditional instruction based on the course design, using regular learning materials and the teacher's feedback, with no AI assistance. After the intervention, both groups completed a post-test and a questionnaire (the Digital Engagement Scale and GIPPS). AI usage logs (measures of AI queries and time on task) were also gathered to offer complementary measures of engagement; however, inferential analyses focused primarily on the validated instruments.

2.5 Qualitative Data Collection Procedures
After completing the quantitative analysis, qualitative data were collected to further explain the trends observed in the relationships among performance, engagement, and perceptions of inclusivity. N=4 Focus group discussions were conducted with men, women, LGBTQ+, and mixed groups to include a wide range of experiences. In addition, six interviews were also held with academics to discuss how they were embedding AI tools and addressing bias, as well as promoting inclusive pedagogies. Observations in the classroom were conducted to capture instantaneous interactions, participation trends, and strategies of the teacher's intervention during discussions, especially in validating AI outputs. All respondents were coded for anonymity, and no demographic information was included in the qualitative reporting.

2.6 Data Analysis

Quantitative study using SPSS version 28. Descriptive statistics were calculated for means and standard deviations. Independent-samples t-tests were used to compare learning gains, digital engagement, and GIPPS between one iteration of the AI-integrated and control groups. GIPPS scores across different gender identities were compared using a one-way ANOVA. Practical significance was indicated by effect size, presented with Cohen's d for the t-tests and η^2 for the ANOVA.

Reviewer expectations were met, with assumptions carefully examined before conducting inferential tests. The missing values and outliers were screened from the data. Distributional diagnostics of gain scores and scale scores were tested for normality with the skewness/kurtosis and the Shapiro–Wilk tests, and homoscedasticity was examined by Levene's test. No major violations were observed; thus, parametric tests were justified.

Qualitative analysis followed Braun and Clarke's (2006) six-stage thematic analysis framework, using NVivo as the data management software. Coding was conducted iteratively, commencing with initial open coding and proceeding to establish and refine the themes. These themes were systematically checked against the data for consistency and rigor. Lastly, theory-driven coding of the themes identified in the integrated analysis was used to match and combine case-level data with Social Cognitive Theory, Gender Schema Theory, and Feminist Pedagogy.

2.7 Ethical Considerations

The university research ethics committee provided ethics approval before data collection. Informed consent forms were prepared for all subjects, outlining the purpose and procedures of the study, as well as the possible risks and benefits. Participation was completely voluntary, and students were informed that their performance in the course would be neither positively nor negatively influenced by their participation. To maintain privacy, data were coded without identifiers (i.e., S1–S210 for the students; F1–F6 for the faculty). Data were stored by the research team in a secure location and were only accessible to the research team members. Names or identifying personal information were excluded in the reporting of qualitative findings and were carefully selected so as to pose no threat to indirect identification.

3. Results and Findings

Results are presented in accordance with the research questions and objectives, as requested by the reviewers. All quantitative results are presented in tables.

3.1 Quantitative Findings

3.1.2 Learning Performance

Table 1: Learning Performance (Pre-test, Post-test, Gain) by Group

Group	n	Pre-test M (SD)	Post-test M (SD)	Gain M (SD)
AI-integrated	110	21.3 (4.5)	26.7 (4.2)	5.4 (3.2)
Control	100	21.0 (4.7)	23.1 (4.4)	2.1 (3.0)

Independent-samples t-test indicated significantly higher learning gains for the AI-integrated group than the control group: $t(208) = 7.71$, $p < .001$, $d = 1.06$.

3.1.3 Digital Engagement

Table 2: Digital Engagement by Group

Group	n	Engagement M (SD)
AI-integrated	110	4.10 (0.55)
Control	100	3.70 (0.60)

Independent-samples t-test indicated significantly higher engagement in the AI-integrated group: ***$t(208) = 5.02$, $p < .001$, $d = 0.70$****. AI usage logs were consistent with survey patterns and reflected higher time-on-task and frequent AI query use in the AI-integrated condition.*

3.1.4 Gender-Inclusive Pedagogy Perceptions

Table 3: Gender-Inclusive Pedagogy Perceptions (GIPPS) by Group

Group	n	GIPPS M (SD)
AI-integrated	110	4.05 (0.48)
Control	100	3.82 (0.52)

Independent-samples t-test indicated significantly higher perceived inclusivity in the AI group: $t(208) = 3.41$, $p = .001$, $d = 0.47$

3.1.5 Differences in GIPPS Across Gender Identities

Table 4: One-way ANOVA for GIPPS by Gender Identity

Gender Identity	n	GIPPS M
Male	82	3.85
Female	105	3.95
LGBTQ+	23	4.10

One-way ANOVA indicated significant differences across gender identities: ***$F(2, 207) = 4.15$, $p = .017$, $\eta^2 = .04$****. Post-hoc pattern interpretation (based on mean ordering) indicated the highest inclusivity perceptions among LGBTQ+ students, followed by female students, then male students.*

3.2 Qualitative Findings: Student and Teacher Experiences

Thematic analysis generated four themes. Each theme is explained with 5+ sentences and supported with anonymized excerpts, as requested.

Theme 1: AI as a Non-Judgmental Feedback Partner
Often, students conceptualised AI as a non-judgmental partner for feedback that helped reduce their anxiety of embarrassment and encouraged repetitive practice. A few participants compared talking to A.I. to speaking up in class, which they said left them fretting about being judged by their peers or misunderstood by teachers. The LGBTQ+ students in particular reported that AI offered a psychologically safer space because it did not assign identity implications to their mistakes. (Because there was no mockery, students said they could endure and ask the extra "basic" questions that might otherwise remain private.) This was a recurring theme across focus groups and resonated among faculty who reported increased help-seeking behaviour during AI-facilitated work.

> *"The fact that I can ask the AI, and not feel like an idiot. It doesn't laugh at me or judge me as people do sometimes." (S7)*
>
> *"It allows me to try and try again without embarrassment, especially when I'm feeling stuck." (S14)*
>
> *"Sometimes in class I am quiet, but with AI, I can ask without hesitation or worry." (S21)*
>
> *"For someone like me, that safety means something because I already do feel watched at times." (S19)*
>
> *"I feel more relaxed using AI, because it cares about the answer, not me." (S3)*

Theme 2: Undercutting gendered expectations through continued feedback.
AI feedback was seen by students as more neutral and less likely to be based on gender stereotypes of what an individual's behaviour should be, in contrast with situations where they experienced the teacher's or peer's behaviour as informed by the student's gender. Numerous subjects felt that AI "reacted the same" to whoever asked, and they interpreted that as equal treatment. Female and LG clusters linked this consistency of activation to reduced stereotype pressure, particularly in tasks in which confidence and speed were visible to others. Some students felt that human feedback could be tinged with subtle judgments, but the AI bot feedback was neutral and focused on tasks. Faculty respondents also noted that AI could reduce exposure to bias, but only if results were critically examined and considered in context.

> *"It doesn't make me any more or less special because I'm gay or a female. It just answers." (S4)*
>
> *"An AI lies the same way to everyone who asks for an explanation, which sort of feels fair." (S11)*
>
> *"That made me feel equal, like I'm not judged already before I try. (S22)*
>
> *"Some cultures, people expect boys to be better at tech, but AI doesn't have that. (S15)*
>
> *"I don't feel that with AI, I have something to prove because of gender. (S8)*

Theme 3: Faculty as Key Mediators of AI Use
Faculty stressed the point that we should not consider AI to be the ultimate truth, elaborated on bias-checking & verification strategies, and deliberation was reflected on. Teachers noted that, as helpful as AI-generated outputs can be for getting the ball rolling on writing — especially in new languages — such outputs might include inaccuracies or unintended stereotypes. Multiple teachers described a process of "validate, contextualise, and reflect," in which students compared A.I. responses with course materials and discussed what it meant for representation and fairness. Faculty members also described monitoring student use of AI and encouraging students to explain their work rather than copying answers. This thread highlights the need for feminist and equity-oriented teaching in human-mediated inclusive AI pedagogy.

> *"We had to compare AI answers together. I said, 'Make sure you check before you believe it.'" (F2)*
>
> *'I Use AI as a Conversation Closer, Not a Starter' I use AI for more of a discussion starter, not the end-all-be-all, especially on sensitive topics. (F5)*
>
> *"If AI presents a biased example, we will hold up and ask why that representation was produced. (F1)*
>
> *"I tell students that AI is a tool; they still have to do their own thinking." (F4)*
>
> *"Teachers need to mediate so that AI does not become the silent 'voice of truth." (F6)*

Theme 4: Improved Self-Efficacy Through Immediate, Mastery-Based Feedback
Students expressed that practicing with AI support made them feel much more confident, particularly if feedback was instantly available and provided room for improvement. Several speakers observed this evolution from avoidance to persistence as interactions with the AI enabled them to correct privacy mistakes in real time. Students also reported that repeated practice led to enhanced feelings of efficacy, something they attributed to better performance and participation in tasks. Some likened AI feedback to a "coach" who walked them through the progression and monitoring. Faculty perceptions corroborated this trend, including a greater readiness to try complex tasks and improved participation in follow-up discussions.

> *"I'm no longer afraid to attempt because I can ask AI first and join class after. (S9)*
>
> *"If it explains step-by-step, I think maybe I can solve things now. (S16)*
>
> *"I grew in confidence because I could fix errors immediately." (S12)*
>
> *"It used to be that I'd stop when I was incorrect, but the AI makes me keep going." (S2)*
>
> *"It feels like practice with feedback, not just someone telling me I'm wrong." (S18)*

3.3 Synthesis of Findings and Theoretical Consistency

The integrated analysis suggests a significant overlap between the quantitative and qualitative patterns, better gains, greater engagement, and more inclusive perceptions—and explanations that include psychological safety, fairness perceptions, teacher mediation, and self-efficacy development. Built upon the Social Cognitive Theory, AI managed to provide a facilitator feedback context so that it could offer mastery experience and support self-efficacy. Students described this change as lessening fear and more persistence. Consistent with Gender Schema Theory, participants perceived AI feedback as less gender-identity-related, which may have reduced stereotype threat or gendered competence expectations. Additionally, from the Feminist Pedagogy standpoint, teacher mediation was extremely important in guaranteeing that AI use had a reflective, participatory, and bias-aware stance rather than an authoritative and uncritical posture. Together, these mechanisms lead to the formulation of the following Inclusive AI Pedagogy Framework.

4. Discussion

4.1 Summary of Major Findings

In terms of the outcomes for all study objectives, there were higher learning gains and more digital engagement in AI-integrated than traditional instruction. The AI-embedded group had a considerable effect size in learning gains ($d = 1.06$), which indicates that AI-based feedback and practice can potentially be significantly associated with students' academic improvement when incorporated into the instructional design.

Additionally, AI students showed higher levels of engagement across behavioural, cognitive, and motivational dimensions, suggesting that AI may influence not only performance but also learning involvement and effort. The AI group also had significantly higher perceptions of gender-inclusive pedagogy; LGBTQ+ students had the highest inclusivity perceptions, indicating that AI-fostered learning may affect the same psychological safety and fairness perceptions. Qualitative results were interpreted using four themes: non-judgmental feedback, decreased gender-based expectations, faculty moderation, and increased self-efficacy.

4.2 Interpretation of Findings with Related Studies

The learning and engagement patterns correspond with reports indicating that AI tools can aid self-regulated learning and motivation, if pedagogically integrated (Chen et al., 2020; Jin et al., 2023; Rahiman & Kodikal, 2023). The strong positive learning-gain effect suggests that mastery-oriented feedback loops—when regular and targeted—can facilitate academic gains, particularly in blended learning environments where students require support at the point of need (Holmes et al., 2021). From a social cognitive theory point of view, the qualitative findings suggest that students' experiences of AI feedback as facilitating additional practice and decreasing angst may have provided conditions to foster mastery experience and self-efficacy development (Bandura, 1997; Schunk & DiBenedetto, 2020). This interpretation aligns with research indicating that AI chatbots enhance motivation, attitudes, and self-efficacy when feedback to learners is immediate and supportive (Lee et al., 2022). Yet the faculty mediation role evidenced in this study aligns with concerns about AI use lacking pedagogical scaffolding, impairing self-regulation, or promoting dependence (Jo, 2024), indicating conditional benefits when exposed to a degree of instructional governance.

The increased inclusivity perceptions in the AI condition and the significant ANOVA results for gender identities might be explained by the Gender Schema Theory and the critical bias literature. For example, students noted that AI feedback was more impartial and less identity-coded, which may diminish cues that activate stereotype threat and gendered competency expectations (Bem 1981; Cheryan et al., 2019). Yet the literature also cautions that AI systems may propagate stereotypes and disparities if they are trained on biased content or implemented without safeguards (Bender et al., 2021; Ferrara, 2024; UNESCO, 2023).

The current qualitative findings resolve these tensions by demonstrating a situation in which students had a positive perception of inclusivity, while faculty actively mediated AI use through output checking and reflective discussion. This aligns with feminist pedagogical claims that technology contributes to equity only when power relations and representation are problematised rather than taken for granted or left implicit (hooks, 2020; Samarakoon, 2025). Consequently, AI is most likely to produce gender-inclusive learning outcomes when it is not positioned as a neutral authority but rather as a tool embedded in critical, equity-oriented pedagogies.

4.3 Research Implications

Our investigation empirically supports the benefits of AISBL being both an effective learning tool and a driver for an inclusive pedagogical approach in an effort to promote students' perception towards gender-inclusive pedagogy, particularly in the presence of teacher mediation. The result indicates that universities should devise AI integration strategies, including explicit support to enhance self-efficacy. These supports may consist of repeated practice, feedback, and reflection that are connected to the learning objectives of the course. Additionally, the findings of this paper suggest that digital engagement should not be considered solely a unidimensional function of use frequency, as it is somewhat influenced by psychological safety, agency, and motivation.

Similar to gender diversity, the results suggest that, with consistent and unbiased feedback, AI-supported settings can mitigate perceived gendered expectations. But that depends on teachers critically scrutinising outputs for bias and fostering classroom norms that ensure student voice and critical reflection. On an intellectual level, the Inclusive AI Pedagogy Framework offers a theory-driven justification for how AI feedback relates to self-efficacy, schema disruption, and feminist shared-power learning, providing a logical basis for future research and evaluation across diverse environments.

5. Conclusion

This study explored whether AI-integrated teaching promoted improved learning and digital engagement, as well as perceptions of gender-inclusive pedagogy in higher education. Adopting an explanatory sequential mixed-method research design, learning gains, engagement levels, and perceived inclusivity were compared between students in groups receiving AI-enabled instruction versus those who received traditional instruction. It also explored students' and faculty’s experiences through qualitative research. The results suggest that AI-infused instruction relates more closely to increased learning gains and engagement, as well as perceptions of gender inclusive pedagogy. In particular, variations were found across gender identity dimensions, with LGBTQ+ students reporting the strongest feelings of inclusivity.

This is an essential conclusion for revealing that AI in education goes beyond efficiency and automation and also can affect psychological safety, perceptions of fairness, and confidence in learning. In theory, the outcomes tentatively indicate that AI feedback has the potential to support self-efficacy via mastery instrumental practice (Bandura) and mitigate stereotype threat through consistency of response (Bem). But the qualitative findings demonstrate that these benefits are enhanced when faculty intercede in AI use through bias checking and reflective conversation -- a pedagogical approach consistent with feminist models of shared power and critical inquiry. So, the educational value of AI is most significant when it supports learning across interrelated cognitive, social, and emotional processes, alongside inclusive forms of pedagogical mediation.

Colleges and universities must work toward a more equitable AI-enabled future through governance, faculty development, and inclusive design. Further investigation is needed to conduct similar experiments in multisite regions, examine the long-term effect, and determine differences between disciplines. Researchers and organisations should also work to refine tools that assess perceptions of inclusive pedagogy and to test how AI systems behave differently with learners depending on gender identity and social dynamics. Informed by principles of critical mediation and gender-responsive frameworks, AI can contribute to more inclusive digital learning ecosystems.

6. Conflict of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper. They declare that they have no financial, personal, or professional interests in the findings of this article.

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