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Undergraduate international students' perceptions of AI-generated feedback: A mixed-methods study at a Canadian university

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Abstract

The rapid adoption of Artificial Intelligence (AI) has sparked debates on its benefits and risks, yet little is known about its impact on trust and role perception in higher education. This study examined how AI-generated feedback influences students' trust in instructors and their perceptions of academic integrity. Building on existing research on AI-human interactions, we explored whether students trust AI-generated assessments more or less than human feedback and how this dynamic affects their learning experience.

Using a mixed-methods approach, this study analyzed student attitudes toward AI in academic settings. The first phase employed a survey to capture broad student perceptions of AI-assisted feedback, while the second phase involved in-depth interviews to explore themes of trust, ethics, and emotional responses. Reflexive thematic analysis (Braun & Clarke, 2021) was applied to identify patterns in students' experiences, highlighting concerns over fairness, depersonalization, and ethical considerations. Participants identified personalized, meaningful feedback as a core instructor responsibility that AI cannot fully replicate. Participants see value in using AI as a supportive tool when its outputs are transparent, guided by educator expertise, and clearly communicated.

Findings underscore the need for structured institutional policies that ensure AI complements rather than replaces human engagement. This paper will explore how universities can develop ethical guidelines that balance AI's efficiency with the critical role of instructor-led mentorship, fostering sustainable and student-centred learning environments.

Introduction

The integration of Artificial Intelligence (AI) into higher education represents a paradigm shift in pedagogical approaches, raising fundamental questions about assessment practices, educational relationships, and institutional values. As universities globally deploy AI-generated feedback systems with increasing frequency, stakeholders must navigate complex tensions between technological efficiency and educational authenticity (Krupiy, 2020; Popenici & Kerr, 2017). Although AI technologies present opportunities for enhanced efficiency and broader implementation across educational contexts, their application in assessment practices has sparked discussions regarding student experiences of meaningful instructor involvement.

Contextual background and significance

The growing presence of AI applications in education has catalyzed widespread debate concerning their appropriate implementation and boundaries. Students' responses to AI-generated feedback demonstrate considerable heterogeneity, contingent upon technological literacy, educational background, and prior digital learning experiences. Arowosegbe et al. (2024) found a positive correlation between students' technological fluency and their receptiveness to AI assessment tools. Nevertheless, this acceptance remains qualified; while students frequently acknowledge efficiency benefits, they also express skepticism regarding AI's capacity to deliver nuanced, contextually informed feedback characteristic of human instruction (Chan & Zary, 2019; Palmer et al., 2023). These concerns underscore a growing tension between technological promise and educational authenticity.

The emotional dimension further complicates AI integration in higher education contexts. While some studies demonstrate AI-generated feedback’s potential to enhance student motivation and engagement (Ji et al., 2022), others report discomfort with mechanistic or impersonal evaluation. This often manifests as alienation from feedback perceived as lacking empathic qualities or interpretive depth (Kim, 2023; Mirbabaie et al., 2022), potentially undermining both motivation and trust in academic systems.

Theoretical framework: Integrating technology acceptance and trust

This study is guided by an integrated theoretical framework that combines the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) with the Five-facet Model of Trust in educational settings (Tschannen-Moran & Hoy, 2000). This synthesis creates a robust analytical lens through which to examine the multidimensional nature of student responses to AI-generated feedback, accounting for both technology acceptance factors and the complex trust dynamics inherent in educational assessment contexts. The UTAUT model explains student acceptance of AI tools via four constructs: performance expectancy (perceived usefulness), effort expectancy (ease of use), social influence, and facilitating conditions. These constructs help interpret variation in student receptiveness to AI feedback (Arowosegbe et al., 2024; Demir & Güraksın, 2022).

Complementing this, Tschannen-Moran and Hoy’s (2000) model identifies five key trust dimensions: benevolence, reliability, competence, honesty, and openness. These are particularly relevant to AI-generated feedback, as research suggests that student trust is strongly influenced by system transparency and explanation quality (Conijn et al., 2023; Sullivan et al., 2023; Zhang et al., 2023). Our framework posits that trust facets mediate UTAUT constructs. This integrated model also captures how AI feedback influences student identity and perceived fairness (Kim, 2023; Keyes et al., 2021), offering a comprehensive lens to explore how emerging technologies reshape the educational experience.

Ethical and institutional implications

Concerns surrounding fairness, identity, and trust are further compounded by ethical and institutional considerations. AI systems may inadvertently reinforce bias or inequality, particularly when deployed without adequate oversight or sensitivity to student identities (Rodrigues, 2020; Schlesinger et al., 2018). Keyes et al. (2021) argue that AI-generated feedback not only assesses but also shapes students’ academic identities, raising profound questions about autonomy and authenticity in learning.

Rodrigues (2020) emphasizes the human rights implications of AI in education, noting how automated grading systems can lead to disenfranchisement and misrepresentation. As controversies around machine grading illustrate, reducing human judgment in student evaluation may compromise the legitimacy of academic assessment. Institutions must therefore develop policies that uphold ethical standards while integrating AI into teaching and learning.

Institutional inconsistency in AI use creates significant challenges across educational contexts as well. Kutty et al. (2024) found that students, instructors, and administrators frequently interpret AI policies differently, generating conflicting expectations. Their study revealed that students consistently requested explicit guidelines, arguing that policy ambiguity undermines fairness.

Despite these concerns, AI technologies offer a genuine promise in enhancing feedback quality and personalization but only when applied with deliberate pedagogical intent. Zhai et al. (2021) and Ma and Siau (2018) demonstrate that AI-supported tools can meaningfully enhance learning outcomes when they are aligned with instructional goals and ethical guidelines, suggesting that the issue is not AI itself but the conditions under which it is deployed. This distinction matters institutionally: as Dignum (2021) argues, realizing that potential requires robust safeguards that actively foster student trust and accountability, rather than assuming technology alone will produce equitable outcomes.

Research gap and study rationale

While literature on AI in education is expanding, much of it focuses on technical capabilities or generalized attitudes toward AI (Ma & Siau, 2018; Zhai et al., 2021). Few studies explore how students emotionally interpret AI-generated feedback or how trust and perceived fairness are affected by these systems. The relational and affective dimensions of learning, which research frequently overlooks, clearly warrant closer attention (Kim, 2023; Keyes et al., 2021).

This study addresses this gap by investigating how technology acceptance intersects with trust dimensions in shaping student perceptions of AI-generated feedback. We examine how AI-generated feedback influences students’ trust in instructors, perceptions of academic fairness, and expectations of personalized support. By drawing on an integrated UTAUT and Five-facet Trust framework, this research provides a more nuanced understanding of how students engage with automated feedback systems within institutional learning environments.

The following section outlines the methodology used, including participant recruitment, data collection strategies, and analytical procedures aligned with the study’s theoretical framework.

Methodology

Our study employed a mixed-methods design to examine students’ perceptions of AI-generated feedback in higher education. Given the limited research on how AI use affects relational dynamics between students and instructors (Seo et al., 2021), a mixed-methods approach was selected to capture both the breadth and depth of student attitudes. Quantitative survey data provided broad insights into patterns of trust and perceived academic integrity, while qualitative interviews offered a deeper understanding of students’ underlying concerns and values. A mixed-methods approach will provide us with a unique and comprehensive lens for understanding the complex nature of student perception of instructors’ AI usage, while increasing the validity and credibility of results through triangulation (Creswell & Plano Clark, 2018).

A mixed-methods design provides researchers with flexibility, allowing them to explore topics in greater depth and breadth through qualitative inquiry (Bryman, 2006). Such an approach is particularly beneficial when studying social topics, such as student perceptions, where numerical and contextual insights are critical (Fetters et al., 2013). Considering that most studies on students' perceptions of instructors' use of AI are quantitative, incorporating a mixed-methods design has enriched our findings by providing deeper insights into students' experiences and attitudes (Sami et al., 2025; Marshik et al., 2024; Zhang et al., 2023)

Participants

Participants were international university students enrolled in undergraduate programs across multiple disciplines from the Arts, Communications, and Social Sciences (ACSS) department of University Canada West (UCW). A purposive sampling strategy was used to recruit a diverse cohort with varying levels of exposure to AI in education. Invitations to participate in the survey were distributed via link and QR code during in-person classes by instructors who did not participate as researchers in our study, and invitations for the interviews were shared with ACSS students via e-mail. As of 2025, UCW has a student body exceeding 11,000 students representing over 100 countries. Ethics approval was obtained prior to the recruitment stage, and the final sample resulted in 170 survey responses and 22 interviewees. The interview participant sample was self-selected from the larger pool of survey respondents. Students signed up for interviews based on time slots to remove the potential bias of students selectively choosing an interviewer. Twenty-two interviews were conducted based on data saturation (once the researchers reached the point at which no new themes had emerged). Qualitative methodologists (Guest et al., 2006) suggest that saturation often occurs within the first 12–20 interviews, especially when the participant group is relatively homogeneous or the study has a focused research question. Conducting 22 interviews allowed for both thematic depth and diversity of perspectives (Braun & Clarke, 2021), helping ensure robustness and credibility of findings.

Research software

Qualtrics was utilized to form the survey screening questionnaire and to analyze the preliminary quantitative data. NVivo was used to code the interviews as well as to conduct thematic analysis. Both Qualtrics and NVivo contributed to the validity and reliability of data collection and analysis in distinct ways. While studies on Qualtrics' validity and reliability are limited, researchers appreciate that Qualtrics offers extensive customization options, including question randomization and embedded data, which enhance the accuracy and consistency of responses (Qualtrics, 2023). Furthermore, Qualtrics complies with major data protection regulations, such as GDPR (General Data Protection Regulation) and HIPAA (Health Insurance Portability and Accountability Act) in the US and PIPEDA (Personal Information Protection and Electronic Documents Act) and FIPPA (Freedom of Information and Protection of Privacy Act) in Canada, ensuring the integrity and confidentiality of collected data. NVivo is quite commonly used as qualitative data analysis software due to its ability to facilitate the coding process, allowing for systematic categorization of data, which improves inter-coder reliability (Kent State University Libraries, n.d.; Kraiwanit et al., 2023; Project Guru, n.d.; Welsh, 2002). Additionally, NVivo's audit trail feature tracks changes and decisions made during analysis, enhancing the transparency and credibility of the research process. While both Qualtrics and NVivo offer features that support the validity and reliability of research, their effectiveness depends on the researcher's expertise and the appropriate application of these tools within the research design.

Data collection procedures

Phase 1

In Phase 1, we sent out an invitation to participate in an online survey (via e-mail and in class). The AI and Ethics in Academia Survey was a 14-item instrument developed to explore students' perceptions of AI use and its ethical implications in academic settings. The survey included both demographic items and Likert-scale questions rated from 1 ("not at all") to 5 ("extremely"), covering emotional responses, ethical evaluations, and views on the role of AI technologies such as ChatGPT in classroom contexts. Questions 1 and 2 asked participants for their name and email information to be able to contact them for the second phase of the project and to identify duplicate responses. Questions 3–6 were focused on collecting demographic information, and we included a test question for validity purposes. Questions 7–11 employed a Likert scale assessing perceptions of the usefulness of AI, the ethics of AI usage in education, perceptions of personalized feedback from instructors, and confidence in the accuracy of AI as grading and feedback tools and related to the primary research questions for the study. Questions 12–14 provided participants with an option to consent to being contacted for the second phase of the project and to express any additional thoughts about the survey content.

Content validity was ensured through a collaborative development process in which three researchers met repeatedly to review and revise survey items for clarity, relevance, and theoretical alignment. Face validity was supported through informal pilot testing with academic colleagues, whose feedback informed final refinements prior to distribution. To assess internal consistency, a reliability analysis was conducted using Cronbach's alpha. The overall scale demonstrated acceptable reliability ($\alpha = 0.68$), with subscales for ethical perception ($\alpha = 0.70$) and emotional reaction ($\alpha = 0.23$) indicating consistent measurement. A lower reliability score of 0.23 can potentially indicate that students' emotional responses were highly varied and suggests that it would be beneficial to include more questions or a more thorough section focusing on emotional response. Although exploratory in nature, the survey's design and psychometric properties support its utility in assessing student attitudes toward the integration of AI in higher education settings.

Phase 2

In Phase 2 of our research study, we conducted semi-structured interviews with 22 participants, all of whom had participated in the first phase of the study and completed the survey questionnaire. Out of 170 survey respondents in the first phase, 106 (62.4%) indicated that they consented to being contacted about a second phase of the study. We emailed invitations for interviews to all the candidates who consented to be contacted. Per Guest et al. (2006) and considering saturation effects, we aimed to interview 15-20 participants. Response rates were initially low, and four rounds of invitations were sent. The interview sample was thus self-selecting. Semi-structured interviews were conducted via Teams video call, focusing on students' emotional reactions, ethical concerns, and perceived roles of instructors and AI. All interviews were video-recorded and transcribed using MS Teams and NVivo. The semi-structured interview protocol comprised 17 questions designed to elicit responses corresponding to the theoretical constructs underpinning this study (see Appendix B for the full question set and framework mapping). Questions were developed with reference to Venkatesh et al.'s (2003) four UTAUT constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions), and the five trust dimensions of benevolence, reliability, competence, honesty, and openness (Tschannen-Moran & Hoy, 2000), ensuring that theoretical alignment was built into the instrument design. Questions addressing social influence (Q7, Q10, Q11) and facilitating conditions (Q11, Q12, Q16, Q17) proved particularly generative, capturing students' nuanced views on institutional responsibility and the perceived ethical double standards of instructor versus student AI use. It is acknowledged, however, that effort expectancy is represented only indirectly through Q4, which probes general attitudes toward AI rather than ease of use specifically. Given that the study focuses on students' responses to instructor AI use rather than their own adoption of AI tools, effort expectancy was considered less central to the research questions.

To enhance validity, interview protocols were pilot-tested with instructor participants and refined for clarity. Interviews were audio-recorded and transcribed verbatim. Data analysis followed a thematic approach, and multiple coders (four) reviewed transcripts to support reliability. An audit trail and reflective notes were maintained to ensure confirmability. Data saturation was considered reached after 22 interviews, as no new themes emerged.

Data analysis

In terms of quantitative data, we focused on basic descriptive statistics results from Qualtrics to compare trust levels and perception of ethics of using AI across participants. In terms of qualitative data, each of the researchers has formed their own thematic schemas and coded the responses manually. Along with the help of a trained research assistant, in the last phase of the study we used reflexive thematic analysis (Braun & Clarke, 2020) and we identified themes touching on AI feedback and student's perception of educators, impact of AI feedback on students, student perspectives on AI usage if educator uses AI, perspectives on AI feedback, and policies on instructor AI use among others.

This in-depth thematic analysis was guided by the theoretical framework proposed by Braun and Clarke (2020), which emphasizes the active role of the researcher in interpreting and engaging with the data, highlighting subjectivity and reflexivity over rigid codebook use or inter-rater reliability. This methodology shaped our analysis by focusing on the dynamic process of meaning-making and fostering a deeper, context-sensitive understanding of the data. Braun and Clarke (2020) outline reflexive thematic analysis as a flexible, iterative process that involves de-

-ep engagement with the data, where researchers actively construct themes through a process of interpretation and reflection of data. The analysis typically follows the following six phases: (1) being familiar with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the report (Braun & Clarke, 2020). Throughout these phases, researchers are encouraged to reflect on their own assumptions, biases, positionality, and the context in which the research is formed and integrated into the observations and analysis. Unlike more positivist approaches that emphasize reliability and coding consistency across researchers, reflexive thematic analysis values the researcher's insights and acknowledges that different researchers may generate different, yet equally valid, interpretations from the same data. As a result, each of us formed and discussed our unique interpretation of the data, including our research assistant.

Ethical considerations

Ethical approval was obtained from the university's institutional review ethics board (REB). Participants provided informed consent, were assured of confidentiality, and could withdraw at any time. Interview data were anonymized using unique code identifiers for each participant (along with their original names erased) and securely stored on a password-protected file on a password-protected computer. Participants were offered a small token of appreciation for completing the survey (e.g., donuts), and interview participants received a $40 honorarium for a one-hour-long interview.

Results

Phase I: Survey Questionnaire

We filtered out incomplete surveys before beginning our analysis. One-hundred and seventy (N = 170) students completed the quantitative and demographic survey that formulated the first phase of our mixed-methods study. The median age of participants in the quantitative survey was 21 and the mean age was 21.9. Eighty-one participants (47.6%) self-identified their gender as male and eighty-six participants (50.6%) self-identified their gender as female, while three respondents (1.8%) chose not to self-identify.

Phase II: Semi-structured Interviews

The semi-structured interviews were held with twenty-two students (n = 22), all of whom had completed the survey questionnaire as part of the first phase. The median age of interview participants was 20.5, and the mean age was 22. Of the 22 individuals interviewed, 12 self-identified their gender as female and 9 self-identified as male, with one respondent choosing not to self-identify. The semi-structured interview questions were related to the research questions of the study:

> RQ1. Is there a relationship between AI-generated feedback and students' perception of educators?
>
> RQ2. How do students perceive the impact of AI-generated grades and feedback on their motivation and self-esteem?
>
> RQ3. How do students perceive students' usage of AI in relation to their instructors' use of AI?
>
> RQ4. Do students view AI-generated grading and feedback as fair and objective? How does this influence their perceptions of institutional AI policy frameworks for instructors?

In relation to our first research question that examined the relationship between the perceptions students have of AI-generated feedback and the perception of the educator, we found that students overall expressed that they very significantly value personalized and detailed feedback from instructors on their assessments. Eighty-three percent of students responded in the survey that they value this type of feedback either "a lot" or "a great deal" (see Figure 1).

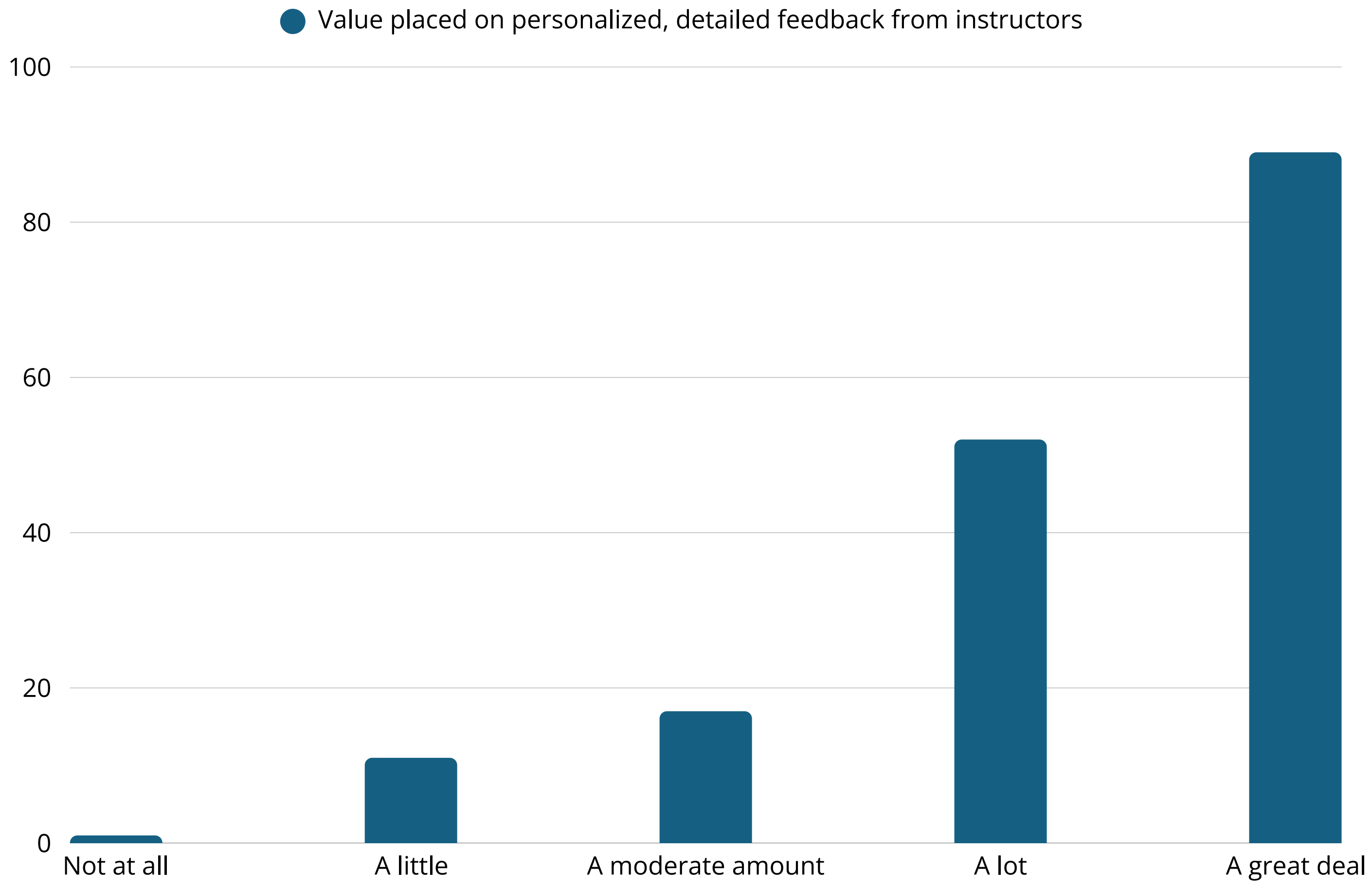

Figure 1. Value placed on personalized feedback from instructors (N = 170).

Students in interviews expressed more dismay and a stronger and more emotional reaction to potentially learning their grade was AI-generated rather than the feedback they received, potentially being AI-generated. Themes of distrust and ethical fairness were central to the responses received here. In terms of distrust, it was noted that AI-generated grading and feedback lack humanity, do not know the circumstances of that class and student, lack the necessary context to appropriately situate the student's performance and is often too general. A majority of students expressed negative feelings toward the idea that an instructor might use AI to grade or provide feedback on their assignment, while at the same time prohibiting students from using generative AI. Student 2 stated that this would be "kind of cheating" by the instructor. Student 20 stated that educators using AI while prohibiting students from using it would cause the student to feel "resentment." Student 6 said they would "maybe [get] a little bit angry" and Student 7 expressed they would feel "all frustrated." Student 12 and 18 were more reserved in their emotional response but noted they would feel "a little bit bad" and "a little low," respectively. There were also discussions on professionalism and many expressed that a crucial part of the instructor's job is to provide students with authentic feedback. Student 20 expressed that "I think that is not doing the job that he or she is getting paid for...It's kind of like a hypocrite thing. Hypocrisy." Student 4 stated, "It means you'll not be an instructor. As the name implies. You're meant to instruct me...Go through what I have read and tell me what I should do better." Student 11 was wary that AI-generated feedback would "make a disconnection...between the professor and the student." Students often used more emotionally detached vocabulary when describing AI: it is a "tool" or "machine," while emphasizing the human connection with their instructors: the educator is "personalized" support and "knows" the student (see Table 1).

Table 1. Student perceptions of instructor compared to AI (n = 22).

How students describe instructor	How students describe AI
Knows me	Tool
Understands context	Machine
Human connection	Disconnected, lacks humanity
Personalized	Doesn’t know context/class

Interview participants expressed overall positive views toward receiving feedback from instructors on their assignments, which aligned with the survey results from Phase 1. Twenty-one participants had a positive and receptive view of receiving feedback on their assignments, and one participant described neutral feelings and that they do not tend to review the feedback. Interview participants identified the purpose of receiving feedback as highlighting direct areas for improvement and the importance of that feedback being personalized to the individual student. Students noted that quality feedback from instructors they have previously received had the characteristic of being detailed and personalized and gave students discernible and distinct areas of their assignment where they could make improvements (see Table 2). Student 7 expressed that good feedback is “not just like a superficial thing…[instead] they are more detailed in their observations, and they say how to…learn and improve.” Student 8 said they appreciated a previous instructor who had been “very precise and very detailed and [the] language [was] very direct and specific. It's not like open-ended sentences or something where you have to figure out the meaning yourself…[it’s] very to the point.” In contrast, students noted that previous feedback they have received was not valuable when it lacked clear focus or direction in terms of identifying a specific part of their work they needed to improve. Most interview participants expressed that they felt there was equal value in both the grade and the feedback they received from instructors, though three students did note that the grade would be more important to them than the feedback, and four students viewed the feedback as more important than the grade.

Table 2. Identified aspects of feedback that are helpful and feedback that is not helpful (n = 22).

Feedback described as helpful	Feedback described as not helpful
Detailed and specific, “to the point”	Lacks clear focus or direction
Identifies something to be improved	Does not identify specific area(s) to improve
Personalized and considers the context and history of the student and class	Overly general or too similar to feedback other students received
Gives students direct steps on how to improve	Students need to figure out what the feedback means

In terms of the second research question, students in the interview stage described negative perceived effects given a hypothetical scenario where they learned the grade or feedback they received on an assignment was generated by AI. Student 15 expressed that they would feel “heartbroken” as “[AI] lacks emotion. It lacks empathy.” Student 3 was concerned that it would mean “my work was for nothing. Like no one is reading my work…all my sacrifice, all my time is for nothing because a real person is not reading my work”, and Student 1 similarly described that “I put in a lot of effort doing that [assignment]. And I expected a real human to just, you know, look at the assignment and grade it.” Additionally, twelve students described that there would be a negative effect on their motivation. Student 4 pointed out that “it might reduce my enthusiasm for school or for being a student.” Student 2 questioned: “Why would I put some effort and do [the assignment] if you're not going to [grade it]? It's like you're not showing interest in teaching me.” Students seemed to perceive a relatively stable or neutral effect on their sense of self-esteem or self-worth. Seven students reported that it may affect their self-esteem, while another nine strongly denied any impact on their self-esteem. For instance, Student 21 described the effect on their self-esteem as: “I think that it would affect my feelings. But I don't think it would affect my self-esteem.”

For the third research question, we explored how students perceived AI and its usefulness and how this intersected with their perceptions of the ethical uses of AI by students and instructors. Over 92% of survey respondents identified that there was at least some usefulness to AI, with 29% of respondents identifying that AI is very useful or extremely useful, signifying at least a neutral or slightly positive view toward the utility of AI overall (see Table 3).

Table 3. Student perception of AI usefulness (N = 170).

Not at all useful (1)	**Slightly useful (2)**	**Moderately useful (3)**	**Very useful (4)**	**Extremely useful (5)**
7.1%(12)	20.1% (35)	42.9% (73)	16.5% (28)	12.9% (22)

Note: The table shows the percentage of respondents who selected the response option and the number of responses for each item in parentheses.

We explored the ways in which students found AI useful both generally and in their work in assignments in the qualitative phase of the study. Perceptions of the utility of AI for education concentrated on its positive effects, mainly as a tool or assistant, while also noting its negative effects in terms of its potential to disconnect educators from students. The most common sentiment from students was that AI could be used as a learning tool for students, essentially playing the role of a personal tutor and providing immediate feedback for revision before submitting the assignment. In this portion of the interviews, some students expressed unprompted empathy for the workload of educators and expressed that AI could also be a tool to reduce the workload and burden on instructors in terms of the amount of preparation and evaluation needed during a course. Student 6 said that “Well, the professors and the instructors have a lot of classes to work on and they have to have a little bit [of] help to get the activities,” and Student 2 noted that the “professor has to leave marks, give scores, and check [a lot of] papers. And that could be overwhelming. I mean, a professor’s job is not easy.” At the same time, participants cautioned that there is a difference between using AI as a tool to assist instructors with feedback compared to instructors relying only on AI-generated feedback. They noted that they viewed educators providing time and attention to connecting with the students through direct, personalized feedback as a critical part of the educator’s role.

Table 4. Student perception of the ethics of AI use by students and instructors (N = 170).

	Not at all ethical (1)	**Slightly ethical (2)**	**Moderately ethical (3)**	**Very ethical (4)**	**Extremely ethical (5)**
How ethical is it for students to use AI for class	23.5% (40)	32.9% (56)	29.4% (50)	10% (17)	4.1% (7)
How ethical is it for instructors to use AI for feedback for assessments	32.4% (55)	25.3% (43)	28.8% (49)	10.6%(18)	2.9% (5)

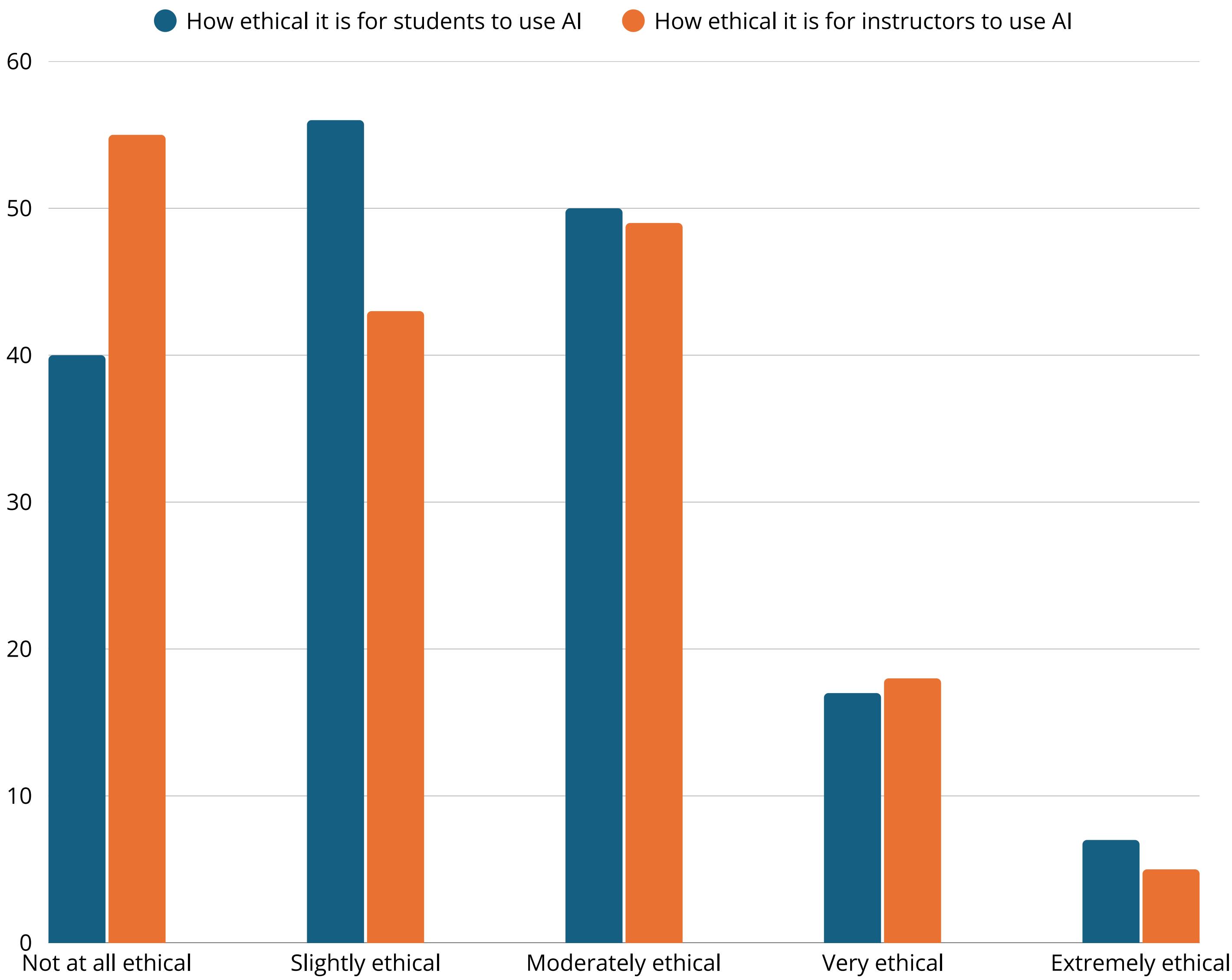

Figure 2. Student perception of the ethics of AI use by students and instructors (N = 170).

In both data sets from Table 4, a small percentage of students identified AI use as very ethical or extremely ethical. Only 14% of students viewed AI use by students for their work to be “very ethical” or “extremely ethical,” and it was a similar value of 13.5% of students who viewed instructors using AI for feedback to be “very ethical” or “extremely ethical” (see Table 4). However, of note is that there was a slightly stronger negative sentiment toward the idea of instructors using AI to provide feedback for assessments (see Figure 2). In this case, 32% of students identified this as “not at all ethical,” whereas only 23% viewed AI use by students as “not at all ethical.” At the same time, it is also worth noting that the percentage of students who responded that students using AI was either “not at all ethical” or only “slightly ethical” was 56.5%, whereas the percentage who responded that instructors using AI was either “not at all ethical” or only “slightly ethical” was 57.6%. There was thus a similar overall negative perception towards the ethics of AI use in education among respondents, regardless of whether that use is by students or instructors.

The common theme that emerged in interviews regarding the appropriate and ethical use of AI was a desire from students for balance. Four participants expressed positive attitudes toward AI use in education, six expressed negative views, and twelve expressed a desire to find balance in how it is utilized. Student 14 stated, “It’s useful if it’s not abused,” and Student 16 indicated that it “depends on how you use it, how you can see the student or the person is using it.” Student 2 expressed that “it's just a matter of finding a balance between all of what you can consider is good or wrong and just act the way you will with integrity and with responsibility... You've got to be responsible to use these kinds of tools.” Many noted that AI is a valuable tool for generating ideas or brainstorming and that this type of use was frequently encouraged by educators. At the same time, participants related to us that many educators had provided warnings and prohibitions on AI usage or had provided students with some guidance for the ethical considerations of AI usage. Turning to the idea of balance, participants noted that overreliance on AI could have consequences for them during their professional career, and many connected this reluctance to rely completely on AI to their own desire to learn and improve. Students appeared to see this as a limitation of AI: while it could assist with the structure of an assignment or be used as a tool, relying only on AI would not serve the desired outcomes or purpose of attending a post-secondary program.

The fourth research question focused on the students’ views toward the fairness, accuracy, and objectivity of AI feedback. Our results show that the confidence that student respondents have in the accuracy of AI-generated grading and feedback is low. Only 11% of students expressed that their confidence in the ability of AI to provide accurate grades and accurate feedback was “a lot” or “a great deal,” while over 58% of students identified their confidence in the accuracy of AI as “not at all” or “a little” (see Table 5). We can see a significant degree of skepticism among student participants as to whether AI is able to generate accurate and reliable grades and feedback for students’ submitted assessments.

Table 5. Student confidence in AI feedback (N = 170).

	Not at all (1)	**A little (2)**	**A moderate amount (3)**	**A lot (4)**	**A great deal (5)**
Confidence in accuracy if the grade/feedback was provided by AI	31.2% (53)	27.6% (47)	30% (51)	7.6%(13)	3.5% (6)

As demonstrated by the quantitative survey, trust in the ability of AI to provide accurate grades and feedback on student assessments was low. This distrust was also present throughout the interviews. Students expressed that AI does not know the context of the class nor the context of the student’s own personal performance, the way an instructor does. Additionally, students expressed that it would not be fair for instructors to use AI to provide feedback without the students knowing or to use AI to provide feedback, but not to allow students to use AI in com-

-pleting their assessments. Participants were more willing to accept AI-generated feedback when an instructor would edit that feedback, when the educator would discuss the feedback verbally with the student, or when the educator was transparent about how they used AI in the feedback and to what extent. Students agreed that there does need to be a formal policy from higher education institutions regulating how instructors use AI in the classroom, and eighteen students expressed that there should be limitations around an instructor’s use of generative AI in grading and feedback.

Discussion and analysis

This study explored student perceptions of AI-generated feedback in higher education, examining its impact on trust in educators, academic motivation, and perceived fairness. Using a mixed-methods design, we combined survey data from 170 students (Phase 1) with in-depth interviews with 22 participants (Phase 2). Drawing from both the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Five-Facet Model of Trust, our findings highlight a nuanced student perspective shaped by expectations of instructor engagement, ethical transparency, and the emotional experience of learning.

Value of human connection in educational feedback

The most striking finding was students' overwhelming valuation of personalized, detailed instructor feedback, with 83% of survey respondents rating this as highly important to their educational experience. This finding underscores the relational dimension of education that transcends purely informational exchange. Feedback is not simply corrective data but a form of recognition that affirms students’ effort and academic identity. When juxtaposed with the low confidence in AI-generated feedback (only 11% expressing high confidence), these results suggest that students perceive human instructor engagement as irreplaceable.

This aligns with Chan and Zary's (2019) observation that while students may acknowledge efficiency benefits of AI tools, they remain skeptical about AI's capacity to deliver contextually informed, nuanced feedback. Our findings extend this observation by showing that skepticism is deeply affective. Students describe the prospect of AI-generated grading in terms of loss of human connection and meaning.

Trust dynamics in AI-mediated education

Our findings revealed a significant trust deficit regarding AI-generated feedback, with 58.8% of survey respondents expressing little to no confidence in its accuracy. This skepticism aligns with the Five-facet Model of Trust (Tschannen-Moran & Hoy, 2000), particularly regarding perceptions of competence and reliability. Interview data contextualized this quantitative finding, suggesting that students' trust concerns stem from perceptions that AI lacks the interpretive depth and contextual understanding that human instructors bring to assessment.

When AI is employed as a supportive tool that enhances instructor efficiency, particularly for generating initial feedback or accelerating grading processes, students often respond positively or neutrally. They view such use as an innovative supplement that respects their learning while preserving the instructor's core responsibilities. These attitudes align with UTAUT constructs of performance expectancy and facilitating conditions, where AI is accepted as long as it improves outcomes without replacing essential educator roles.

Conversely, if AI appears to substitute meaningful instructor engagement, students report a decline in trust. This is particularly evident when feedback lacks personalization, clarity, or contextual relevance. Drawing on Tschannen-Moran and Hoy (2000), such instances activate the trust dimensions of benevolence, reliability, and openness; the absence of perceived human effort signals a lack of care and commitment, eroding confidence in the educator’s professional investment. The lack of educator involvement in feedback delivery leads students to question the educator’s role in the learning process, which many consider central to teaching and a core responsibility. These findings are echoed by Conijn et al. (2023), who noted that transparency and explanation quality significantly influence student trust in AI feedback systems.

Ethical tensions and professional responsibilities

The survey data revealed comparable but distinctly patterned ethical concerns regarding AI use by students versus instructors. While overall negative perception levels were similar (56.5% for student use vs. 57.6% for instructor use), the proportion of students who viewed instructor use as "not at all ethical" was notably higher (32.4% compared to 23.5% for student use). These findings suggest that students may have more negatively polarized perceptions of the ethics of instructors using AI than their perceptions of the ethics of student use. Through our semi-structured interviews, we found that students often emphasized themes of trust, responsibility, and expertise in their views toward instructor use of AI, and it is possible that these are factors that would account for the more negatively polarized result. Students frequently framed instructor responsibilities in terms of professional obligation and educational integrity. This aligns with Krupiy's (2020) assertion that AI applications in evaluative roles raise fundamental questions about institutional values and educational relationships. Students articulated concerns about the potential depersonalization of feedback and the diminishment of instructor engagement, concerns that echo Mirbabaie et al.'s (2022) findings regarding the alienating effects of mechanistic evaluation.

A subset of students expressed conditional acceptance based on transparency, purpose, and extent of use. For these learners, as long as feedback quality meets expectations, the mechanism behind it matters less. This neutral stance reinforces the diversity of student values and highlights the importance of individualized pedagogical approaches.

Impact on student motivation and self-esteem

The emotional and psychological responses to AI-generated feedback varied across participants. The survey indicated only 11% of students expressed high confidence in AI-generated feedback, suggesting widespread skepticism. In interviews, some students appreciated the speed, objectivity, and efficiency of AI evaluations, reporting increased motivation and confidence, while many described negative effects. Impersonal or overly critical AI feedback lacked humanity and was often perceived as demotivating, contributing to reduced effort and lowered self-esteem. These students described a sense of alienation from the learning process, where feedback felt decontextualized and unreflective of their unique efforts.

This emotional response underscores the central role of trust and relational pedagogy in fostering learner motivation. Students desire feedback that acknowledges their growth, effort, and challenges, elements which AI cannot fully replicate. Theoretically, this highlights the interplay between UTAUT's performance expectancy and the trust dimension of benevolence (Tschannen-Moran & Hoy, 2000): students are more likely to accept AI when it is experienced as supporting, rather than displacing their emotional investment in learning.

Student AI use in response to instructor AI use

Awareness that instructors may use AI for feedback prompts complex student reflections about their own AI usage. Survey data indicated ethical concerns about AI use in education generally, while interviews provided deeper insights. Many students see AI as a valuable tool for brainstorming and improving clarity, provided it is used ethically and in moderation. However, others express concern about becoming overly dependent on AI or receiving unfair treatment, especially if instructors prohibit student use while relying on AI themselves.

Recent research by Kutty et al. (2024) supports our findings by revealing student concerns about ethical inconsistencies when instructors use AI tools while simultaneously restricting student access. This highlights the need for equitable AI policies developed collaboratively with student input to address these perceived double standards. This tension reveals a perceived ethical double standard that undermines students' sense of academic fairness. According to the trust model, this reflects diminished perceptions of openness and honesty when institutional norms appear inconsistent. The strong correlation between perceptions of student and instructor AI use ethics suggests that individual attitudes toward educational AI are relatively consistent, though qualitative interviews revealed more nuanced perspectives.

Perceptions of fairness and policy recommendations

Students' views on the fairness of AI-generated feedback and grading are conditional and highly context-sensitive. Feedback is generally seen as fair when it is detailed, transparent, and aligned with clearly defined rubrics. Vague or generic comments are frequently perceived as unfair or untrustworthy, particularly in subjective assignments. Students desire clarity about how AI systems are trained, how they evaluate work, and whether instructor oversight is present.

Emotional responses to AI-generated feedback also include frustration, disappointment, and in some cases, ethical discomfort. Several participants framed instructor reliance on AI as hypocritical, especially when instructors used AI covertly or maintained restrictive policies for student AI use. These responses reflect a moral dimension of fairness and trust that institutions must navigate carefully.

Faculty perspectives reinforce the urgent need for institutional clarity and ethical alignment. Tran et al. (2025) found that academic staff navigate conflicting expectations while expressing concern about ambiguous boundaries surrounding AI use in teaching. Concerns around guidelines and policies created by institutions are that they are vague, inconsistently applied, or vary too much across institutions (Azevedo et al., 2024; Kutty et al., 2024). Students connected this to principles of fairness that work both ways and show respect for the rights of students. Many of them are paying increasingly high tuition fees while also facing higher costs of living in Canada in recent years. Participants agreed that clear limitations are needed for instructors in terms of guidelines and restrictions that clarify how instructors may or may not use AI to provide feedback, as well as clear examples of when AI would be acceptable. They noted that this is important for both students and educators. This emphasizes the importance of collaborative policy development involving both educators and learners to ensure fairness and mutual trust.

Implications for educational policy and practice

Our findings have significant implications for institutional approaches to AI in higher education. The clear student preference for human engagement alongside recognition of AI's utility suggests the need for balanced policies that position AI as complementary rather than replacement technology. Policy recommendations emerging from these findings include:

1. Transparency requirements: Clear guidelines requiring disclosure of AI involvement in assessment processes;

2. Human oversight standards: Expectations for meaningful human review of AI-generated feedback before it reaches students;

3. Educational relationship preservation: Protection of the relational dimensions of education that students clearly value;

4. Equal standards: Consistent policies for student and instructor AI use to preserve fairness and trust.

These recommendations align with Dignum's (2021) emphasis on institutional safeguards that foster student trust and accountability in AI-integrated education, and mirror concerns expressed by academic staff across various institutions. Tran et al. (2025) discovered that while faculty remain cautiously optimistic about AI's pedagogical benefits, they worry about inconsistent policies, insufficient institutional support and potential threats to educational authenticity, which further emphasizes the necessity of structured guidelines that balance ethical integrity with transparent AI implementation.

Limitations and future research directions

Several limitations warrant consideration when interpreting these findings. Our survey sample (N = 170) provides substantial quantitative insights, while the interview portion (n = 22) offers more constrained generalizability, necessitating the integration of both data sources throughout this analysis. First, in Phase 1, we assessed the internal consistency of the survey items by conducting a reliability analysis using Cronbach’s alpha. The low reliabil-

-iability observed for emotional reaction ($\alpha = 0.23$) suggested that some students may not have fully understood the questions related to emotional responses, possibly due to language barriers. In the future, it would be beneficial to further evaluate the emotion-related subscale by examining the stability of scores across interviews and checking for reverse-coded items; items that do not align well with the overall subscale could then be removed. The study could also be repeated to compare results, and findings could be examined alongside those of similar studies.

Next, we did not differentiate between students' beliefs in the accuracy of AI-generated grading versus AI-generated feedback overall. However, our semi-structured interviews did reveal some differences in how students perceive an AI-generated grade compared to how they perceive AI-generated feedback, as discussed in the results for RQ1. Future studies may also be able to identify this differentiation in perception through quantitative methods by including it in the survey questionnaire itself and focusing on highlighting specific differences as to how students interpret AI-generated grades versus AI-generated feedback.

Additionally, despite efforts to minimize social desirability bias, participants' responses may still reflect perceived normative expectations regarding AI use in academia. We caution that although we ensured that the students participating in the survey were not our current students to minimize social desirability bias, the effects of this bias may still be present. Social desirability bias can result in participants underreporting behaviors, views, or activities that are perceived by others to be undesirable (Krumpal, 2013). Nederhof (1985) identified both self-deception and other forms ofdeception as factors that could lead to social desirability bias. Nederhof additionally notes that while other-deception can be reduced, it is not always possible to do this with self-deceptive social desirability bias. In order to mitigate the effects of other-deception social desirability bias, we included information in our survey consent forms and verbally that the students' disclosures in the survey would be highly confidential, not be accessible to their current professors or anyone outside of the research group, and would also be de-identified for analysis and reporting. We did not ask students to think about their own AI use, but rather to more neutrally and generally think about their own perceptions of student and instructor AI use and ethics. Some students did discuss their own AI use of their own volition in interviews, despite never being directly asked. Nonetheless, other-deception social desirability bias may persist as the responses were confidential, but not fully anonymous to the researchers in the study, as our study design necessitated the collection of some identifying information for the interview phase of our mixed-methods study. The students were also aware of our appointments as Assistant Professors at the university at the time of the study. Additionally, the nature of the question in relation to AI and its ethical use in an educational context, while students are enrolled at the university, may have been perceived as a 'threatening question' by participants (Sudman & Bradburn, 1974).

The self-selected interview sample may also overrepresent students with strong opinions about AI in education. Furthermore, the study was conducted at a single institution with a solely international student demographic profile, which constrains generalizability. Finally, survey measures were adapted rather than validated from existing questionnaires, which may affect reliability.

Future research should address these limitations through larger-scale studies with more diverse participant pools. Additional areas for exploration include how disciplinary contexts influence perceptions of AI-generated feedback, as assessment norms and expectations vary significantly across academic fields. Longitudinal studies could examine how student perceptions evolve as AI tools become more sophisticated and widespread in educational settings. Finally, experimental designs comparing student responses to identical feedback attributed to either human instructors or AI systems could provide valuable insights into attribution effects on feedback reception.

Conclusion

This study demonstrates that international undergraduate students interpret AI-generated feedback as a relational and ethical experience. Student acceptance of AI in assessment is mediated by perceptions of transparency, professional responsibility, and the visibility of human oversight.

Theoretically, the study makes two contributions: it demonstrates the analytical value of pairing UTAUT (Venkatesh et al., 2003) with the Five-Facet Model of Trust (Tschannen-Moran & Hoy, 2000) to capture both the utilitarian and relational dimensions of student responses to AI; and it foregrounds international students as an underrepresented population whose experiences complicate assumptions about the generalizability of existing findings.

These contributions open productive directions for future inquiry: longitudinal studies tracking how trust evolves as AI tools mature, and comparative work across disciplines to test whether the preference for relational feedback is context-specific. The suggested directions align with the interdisciplinary research priorities outlined in the AIEOU shared research agenda (Ratner et al., 2026), which foregrounds questions of trust, equity, and human-centred AI implementation in educational contexts.

What this study ultimately suggests is that the challenge of integrating AI into higher education assessment is less technical than it is relational. The conditions which students have identified offer a transferable evaluative lens that extends beyond this single institutional context and that sustainable AI implementation depends less on the sophistication of the tool than on the trust students place in the people and institutions deploying it.

References

Arowosegbe, A., Alqahtani, J. S., & Oyelade, T. (2024). Perception of generative AI use in UK higher education. *Frontiers in Education*, *9*. https://doi.org/10.3389/feduc.2024.1463208

Azevedo, L., Mallinson, D. J., Wang, J., Robles, P., & Best, E. (2024). AI policies, equity, and morality and the implications for faculty in higher education. *Public Integrity*, 1–16. https://doi.org/10.1080/10999922.2024.2414957

Braun, V., & Clarke, V. (2020). One size fits all? What counts as quality practice in (reflexive) thematic analysis? *Qualitative Research in Psychology*, *17*(4), 1-25. https://doi.org/10.1080/14780887.2020.1769238

Braun, V., & Clarke, V. (2021). Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counselling and Psychotherapy Research, 21*(1), 37-47. https://doi.org/10.1002/capr.12360

Bryman, A. (2006). Integrating quantitative and qualitative research: How is it done? *Qualitative Research, 6*(1), 97–113. https://doi.org/10.1177/1468794106058877

Chan, J., & Zary, N. (2019). Applications and challenges of implementing artificial intelligence in medical education: Integrative review. *JMIR Medical Education, 5*(1), Article e13930. https://doi.org/10.2196/13930

Conijn, R., Gulikers, J., & Snijders, C. (2023). Student trust in AI feedback for writing: Do grading transparency and explanation matter? *British Journal of Educational Technology, 54*(4), 848–865. https://doi.org/10.1111/bjet.13299

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research.* (3rd ed.) SAGE Publications.

Demir, K., & Güraksın, G. E. (2022). Determining middle school students' perceptions of the concept of artificial intelligence: A metaphor analysis. *Participatory Educational Research, 9*(2), 297-312. https://doi.org/10.17275/per.22.41.9.2

Dignum, V. (2021). The role and challenges of education for responsible AI*. London Review of Education, 19*(1), 1-11. https://doi.org/10.14324/lre.19.1.01

Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs – Principles and practices. *Health Services Research, 48*(6, Pt. 2), 2134–2156. https://doi.org/10.1111/1475-6773.12117

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field methods, 18*(1), 59-82. https://doi.org/10.1177/1525822X05279903

Ji, H., Han, I., & Ko, Y. (2022). A systematic review of conversational AI in language education: focusing on the collaboration with human teachers. *Journal of Research on Technology in Education*, *55*(1), 48–63. https://doi.org/10.1080/15391523.2022.2142873

Kent State University Libraries. (n.d.). NVivo: Qualitative data analysis software. Retrieved May 12, 2025, from https://www.library.kent.edu/nvivo

Keyes, O., Hitzig, Z., & Blell, M. (2021). Truth from the machine: Artificial intelligence and the materialization of identity. *Interdisciplinary Science Reviews, 46*(1-2), 158-175. https://doi.org/10.1080/03080188.2020.1840224

Kim, S. (2023). Change in attitude toward artificial intelligence through experiential learning in artificial intelligence education. *International Journal on Advanced Science, Engineering and Information Technology, 13*(5), 1953-1959. https://doi.org/10.18517/ijaseit.13.5.19039.

Kraiwanit, T., Limna, P., & Siripipatthanakul, S. (2023). NVivo for social sciences and management studies: A systematic review. *Advance Knowledge for Executives, 2*(3), 1-11.

Krumpal, I. (2013). Determinants of social desirability bias in sensitive surveys: A literature review. *Quality & Quantity, 47*, 2025–2047. https://doi.org/10.1007/s11135-011-9640-9

Krupiy, T. (2020). A vulnerability analysis: Theorising the impact of artificial intelligence decision-making processes on individuals, society, and human diversity from a social justice perspective. *Computer Law & Security Review, 38*(1), Article 105429. https://doi.org/10.1016/j.clsr.2020.105429

Kutty, S., Chugh, R., Perera, P., Neupane, A., Jha, M., Li, L., Gunathilake, W., & Perera, N. C. (2024). Generative AI in higher education: Perspectives of students, educators and administrators. *Journal of Applied Learning & Teaching, 7*(2). https://doi.org/10.37074/jalt.2024.7.2.27

Ma, Y., & Siau, K. L. (2018). Artificial intelligence impacts on higher education. *MWAIS 2018 Proceedings*, 42. http://aisel.aisnet.org/mwais2018/42

Marshik, T., McCracken, C., Kopp, B., & O'Marrah, M. (2024). Student and instructor perceptions and uses of artificial intelligence in higher education. *Teaching of Psychology*, *51*(4), 1453-1469. https://doi.org/10.1177/00986283241299745

Mirbabaie, M., Brünker, F., Möllmann, N. R., & Stieglitz, S. (2022). The rise of artificial intelligence–understanding the AI identity threat at the workplace. *Electronic Markets, 32*(1), 73-99. https://doi.org/10.1007/s12525-021-00496-x

Nederhof, A. (1985). Methods of coping with social desirability bias: A review. *European Journal of Social Psychology, 15*(3), 263–280. https://doi.org/10.1002/ejsp.2420150303

Palmer, E., Lee, D., Arnold, M., Lekkas, D., Plastow, K., Ploeckl, F., Srivastav, A., & Strelan, P. (2023, December 3-6). Findings from a survey looking at attitudes towards AI and its use in teaching, learning and research [Pecha Kucha presentation]. *Australasian Society for Computers in Learning in Tertiary Education Conference*, Christchurch, New Zealand. https://doi.org/10.14742/apubs.2023.537

Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning, 12*(1), 1-13. https://doi.org/10.1186/s41039-017-0062-8

Project Guru. (n.d.). Explaining validity and reliability of qualitative data in NVivo. Retrieved May 2, 2025, from https://www.projectguru.in/explaining-validity-reliability-qualitative-data-nvivo/

Qualtrics. (2023). Qualtrics survey platform overview. https://www.qualtrics.com/support/survey-platform/survey-module/survey-tools/survey-tools-overview/

Ratner, S., Nie, D., Williams, R., Wonnacott, E., & Trefethen, A. (2026). AIEOU shared research agenda 2026. Department of Education, University of Oxford. https://doi.org/10.5287/ora-nogo0ra4e

Rodrigues, R. (2020). Legal and human rights issues of AI: Gaps, challenges, and vulnerabilities. *Journal of Responsible Technology, 4*(1), Article 100005. https://doi.org/10.1016/j.jrt.2020.100005

Sami, A., Tanveer, F., Sajwani, K., Sajwani, N., Kiran, N., Javed, M. A., Ozsahin, D. U., Muhammad, K., & Waheed, Y. (2025). Medical students' attitudes toward AI in education: Perception, effectiveness, and its credibility. *BMC Medical Education, 25*, Article 82. https://doi.org/10.1186/s12909-025-06704-y

Schlesinger, A., O'Hara, K. P., & Taylor, A. S. (2018, April). Let's talk about race: Identity, chatbots, and AI. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3173574.3173889

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. *International Journal of Educational Technology in Higher Education, 18*, Article 54. https://doi.org/10.1186/s41239-021-00292-9.

Sudman, S., & Bradburn, N. M. (1974). Response effects in surveys: A review and synthesis. University of Chicago, National Opinion Research Center.

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning & Teaching, 6*(1), 31-40. https://doi.org/10.37074/jalt.2023.6.1.17.

Tran, C., James, B., Allen, V., de Castro, R. O., & Sanin, C. (2025). Using generative artificial intelligence in learning and teaching: An empirical analysis on academic staff's perspectives. *Journal of Applied Learning & Teaching, 8*(1), 78-90. https://doi.org/10.37074/jalt.2025.8.1.23

Tschannen-Moran, M. & Hoy, W. K. (2000). A multidisciplinary analysis of the nature, meaning, and measurement of trust. *Review of Educational Research, 70*(4), 547-593. https://doi.org/10.3102/00346543070004547

Venkatesh, V., Morris, M., Davies, G. & Davis, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Welsh, E. (2002). Dealing with data: Using NVivo in the qualitative data analysis process. *Forum: Qualitative Social Research, 3*(2). https://doi.org/10.17169/fqs-3.2.865

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

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. *International Journal of Educational Technology in Higher Education, 20*, Article 49. https://doi.org/10.1186/s41239-023-00420-7

Appendix A

Q#	Interview Question
1 – 6	Demographic information: name, email address, age, gender, ethnicity, program of study
	Validity test question
7	Please rate how useful you find ChatGPT/AI on a scale of 1-5 (1 means not at all useful, and 5 means extremely useful).
8	In terms of ethics, how ethical do you think it is for students to use ChatGPT/AI in the classroom on a scale of 1-5 (1 means not at all ethical, and 5 means extremely ethical).
9	In terms of ethics, how ethical do you believe ChatGPT/AI use is by instructors to provide feedback to students on their assignments on a scale of 1-5 (1 means not at all ethical, and 5 means extremely ethical).
10	In terms of feedback, please rate how much you value detailed, personalized instructor feedback on a scale of 1-5 (1 means don't value at all, and 5 means value a great deal).
11	If you learned that your grade and feedback were provided by AI, how confident would you be in their accuracy? Please provide your rating on a scale of 1-5 (1 means not confident at all, and 5 means a great deal of confidence).
12 – 14	Consent to be contacted for phase 2, additional comments, and submission confirmation

Appendix B

Semi-Structured Interview Questions Mapped to Theoretical Framework

The table below presents the semi-structured interview questions that were used in Phase 2 of the study, mapped to the corresponding constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) and the Five-Facet Model of Trust (Tschannen-Moran & Hoy, 2000).

Q#	Interview Question	RQ	UTAUT Construct (Venkatesh et al., 2003)	Five-Facet Trust Dimension (Tschannen-Moran & Hoy, 2000)
1	Tell me about yourself, your program of study and career plans.	*Q1 serves as a contextualizing/demographic question and does not map to either framework.*		
2	How do you feel about feedback you receive on assignments from instructors generally?	RQ1	**PE**	**BEN COM**
3	When you get your paper back, do you pay more attention to the grade or the feedback, or both?	RQ1, RQ2	**PE**	**COM REL**
4	What is your general attitude toward AI — do you think it is useful or harmful, for general and academic purposes?	RQ3	**PE EE**	**—**
5	Can you describe a time when instructor feedback was particularly valuable? What stood out?	RQ1	**PE**	**COM BEN REL**
6	Can you describe a time when feedback was not useful, or perhaps damaging to your motivation?	RQ2	**PE**	**BEN REL**
7	If you found out that an instructor was using AI to give you written feedback, how would you feel?	RQ1, RQ2	**PE SI**	**BEN HON OPN**
8	Would it make a difference if the AI generated the written feedback versus just the grade?	RQ4	**PE**	**COM REL HON**
9	Do you think AI-generated grades are fair or objective?	RQ4	**PE**	**COM REL HON**
10	If you knew your instructor used AI for feedback or grading, would it change how you view or respect them?	RQ1	**SI**	**BEN HON OPN**
11	Would your feelings differ if the instructor allowed vs. prohibited student AI use while using it themselves?	RQ3, RQ4	**SI FC**	**HON OPN**
12	Is there a difference between an instructor using AI to generate classroom activities vs. giving feedback or grades?	RQ3	**FC**	**COM OPN**
13	Would knowing an instructor uses AI for feedback affect your motivation or effort on assignments?	RQ2	**PE SI**	**BEN REL**
14	Would it affect your self-esteem?	RQ2	**PE**	**BEN**
15	Have your instructors discussed AI use positively or negatively and has that influenced how you feel about it?	RQ3	**SI**	**OPN**
16	Do you think there should be a policy on how instructors use AI?	RQ4	**FC**	**HON OPN REL**
17	What should that policy include or look like?	RQ4	**FC**	**HON OPN REL BEN COM**

Appendix B was developed with the assistance of Claude (Anthropic, 2025), under the direction of the authors.

Appendix B cont.

Abbrevitation Key

UTAUT Constructs (Venkatesh et al., 2003)
PE (Performance Expectancy): the degree to which students believe AI-assisted feedback will improve their academic performance.
EE (Effort Expectancy): the perceived ease of using or interacting with AI-generated feedback.
SI (Social Influence): the extent to which students are influenced by peers, instructors, or institutional norms regarding AI use.
FC (Facilitating Conditions): the presence of institutional support, policies, and infrastructure that enable or constrain AI use in assessment.

Five-Facet Trust Dimensions (Tschannen-Moran & Hoy, 2000)
BEN (Benevolence): the belief that the instructor genuinely cares about the student’s wellbeing and learning.
REL (Reliability): the consistency and dependability of feedback quality and instructor conduct.
COM (Competence): the confidence that the instructor (or AI) has the knowledge and skill to provide accurate, meaningful feedback.
HON (Honesty): the perception that feedback is truthful, unbiased, and ethically delivered.
OPN (Openness): the degree to which instructors and institutions are transparent about how AI is used in assessment processes.