Teachers' Perceptions of Conditional Equity in Artificial Intelligence Use

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***Abstract*— Equitable artificial intelligence (AI) use depends on the conditions under which learners can benefit from it. This descriptive Scholarship of Teaching and Learning (SoTL) inquiry examined perceptions of 32 in-service educators enrolled as students in two sections of a master's course. Five four-point Likert-type items and one open-ended question were analyzed using descriptive statistics, participant-level cross-tabulations, and focused thematic analysis. Among 27 participants endorsing personalized AI support as potentially reducing educational inequalities, 26 (96.3%) rejected at least one enabling condition related to access, school resources, or teacher preparation; 14 (51.9%) rejected all three. Linked written responses elaborated these conditions and cultural and linguistic responsiveness. Two participants described potential benefits in writing despite disagreeing with the personalized-support item. Conditional equity serves as an interpretive label linking anticipated benefits to the conditions governing their realization. The findings suggest priorities for course reflection and implementation planning within the limits of a small convenience sample; they do not establish learning gains or equitable outcomes.**

Keywords*— *artificial intelligence in education, educational equity, generative artificial intelligence, teacher perceptions, teacher readiness

I. Introduction

Artificial intelligence (AI), especially generative AI (GenAI), offers functions that may support learning, including feedback, explanations, and personalized assistance. Prior work has proposed a methodology for examining student–chatbot interactions during peer-feedback activities [1] and identified goal setting, feedback, and personalization as design principles for AI chatbots supporting self-regulated learning [2]. Research on inclusive AI also highlights accessibility and support for diverse learners [3].

Educational equity involves more than distributing devices or accounts. Differences in connectivity, paid features, language support, accessibility, and opportunities to evaluate outputs can limit meaningful participation. Research on inclusive AI connects possible gains in accessibility and autonomy with constraints involving infrastructure, accuracy, educator readiness, and bias [3].

Teachers' judgments offer a situated perspective on these conditions. Teacher educators report instructional promise alongside questions about ethics, assessment, and foundational skills [4]. School-level support is associated with teachers' GenAI self-efficacy, valuing, and integration [5]. Such perceptions can inform implementation decisions, although they do not directly measure students' access, AI use, or learning outcomes.

We use conditional equity to describe the relationship between an AI application's perceived equity-supportive potential and the conditions needed to realize it. This interpretation draws on postdigital accounts of agency distributed across learners, educators, tools, policies, and institutional expectations [6], and design-oriented work connecting educational value to scaffolding and task structure [7]. Within existing digital equity and sociotechnical perspectives, the term focuses attention on a particular anticipated benefit and the conditions governing who can receive it. It is an organizing label for this relationship, not a new equity framework or a validated construct.

This exploratory SoTL inquiry examines graduate students' understandings of equitable AI use as an aspect of their professional learning. Their survey ratings and written explanations provide a basis for reflecting on teaching priorities in the educational technology course. Two questions guide the analysis:

- What conditions do participating teachers identify as necessary for equitable AI use in education?
- How do they reconcile AI's perceived equity-supportive potential with concerns about access, resources, and teacher preparedness?

II. Method

A. Participants and Context

Participants were 32 in-service educators enrolled as students in two sections of a first-year master's course in educational technology in Eastern Canada. This cross-sectional course inquiry examined their understandings of AI equity to inform reflective teaching practice; it did not assess change over time. Participants worked across elementary and secondary settings and taught STEM (n = 26), humanities and languages (n = 17), arts (n = 11), health (n = 2), and physical education (n = 2). Multiple subject selections were permitted.

B. Instruments

The course survey was adapted from an instrument examining educators' perceptions of AI-related risks [8]. Five items were selected for their relevance to material access (equal access and cost disparities), institutional capacity (school resources), educator capacity (teacher preparation), and anticipated distributive benefit (personalized support). Although the source instrument addressed higher education, these items referred to students and schools in participants' teaching contexts. This adaptation supports an exploratory account of perceived conditions; it does not establish a validated equity measure.

Items used a four-point Likert-type response scale: 1 (strongly disagree), 2 (disagree), 3 (agree), and 4 (strongly agree). The absence of a neutral midpoint may encourage directional responses, with effects depending on the question and respondent [9], [10]. Items were analyzed separately because they represent distinct conditions. One open-ended question asked how AI access and use might promote or hinder equitable opportunities for students from diverse socioeconomic and cultural backgrounds.

C. Procedure and Analysis

The survey supported quality assurance, program improvement, and reflective teaching practice. The institution's Research Ethics Board exempted the project from review. Students were informed of these purposes and the use of de-identified responses and indicated consent by proceeding. Recruitment was by convenience within the two course sections. Students who completed the survey earned a 2% bonus mark; no alternative activity offered equivalent credit. Responses were de-identified before analysis.

JASP (Version 0.96) was used to calculate item frequencies, percentages, means, and standard deviations. All 32 respondents had complete data for the five items. Table I combines ratings 1–2 as disagreement and 3–4 as agreement; means and standard deviations retain the original four-point scoring. Participant-level cross-tabulations examined co-occurrence of personalized-support endorsement with rejection of equal access, sufficient resources, and adequate preparation, and with endorsement of cost disparities. Among participants who endorsed personalized support, we counted those who disagreed with at least one—and those who disagreed with all three—statements about equal access, sufficient school resources, and adequate teacher preparation. Percentages were calculated within this group and rounded to one decimal place. Analyses were descriptive; no statistical significance tests were conducted.

The single open-ended item received focused thematic analysis at a descriptive, semantic level [11]. Two coders from the research team jointly reviewed and coded all 32 responses, refining codes through iterative reading and resolving disagreements through discussion. Codes addressed access and affordability, equity-supportive potential, institutional readiness and public provision, and cultural or linguistic representation. Responses could receive multiple codes. Excerpts illustrate themes and agreement or variation between response types.

De-identified IDs (S1–S32) linked written responses and assigned codes to the corresponding survey records. Integration compared item distributions with thematic patterns, then examined individual ratings alongside written explanations. This enabled examination of both alignment and differences between response types. Cultural and linguistic accounts extended the closed-ended items, which did not directly measure these dimensions.

III. RESULTS

A. Equity Potential and Readiness Constraints

Table I shows broad endorsement of anticipated benefit alongside perceived implementation shortfalls. Twenty-seven participants (84.4%) agreed that personalized AI support could narrow educational inequalities. Teacher preparation received the strongest negative rating: 29 (90.6%) disagreed that teachers were adequately trained to address equity issues.

TABLE I. DESCRIPTIVE RESPONSES TO THE FIVE EQUITY-RELATED ITEMS

Item	M (SD)	Disagree n (%)	Agree n (%)
All students have equal access to AI tools	1.97 (0.65)	26 (81.25)	6 (18.75)
Schools provide sufficient resources for equitable AI access	2.13 (0.75)	21 (65.63)	11 (34.37)
Cost barriers create disparities between well-funded and under-resourced schools	3.06 (0.56)	4 (12.50)	28 (87.50)
AI helps narrow educational inequalities through personalized support	2.97 (0.54)	5 (15.63)	27 (84.37)
Teachers are adequately trained to address equity issues in AI use	1.66 (0.75)	29 (90.63)	3 (9.38)

Twenty-six participants (81.3%) disagreed that students had equal access, 21 (65.6%) disagreed that schools provided sufficient resources, and 28 (87.5%) endorsed cost-related disparities. These responses identify perceived constraints on access, affordability, institutional provision, and educator capacity. They do not establish the actual resources available in participants' schools.

Among the 27 participants endorsing personalized support, 22 (81.5%) also rejected equal access, 17 (63.0%) rejected sufficient school resources, and 24 (88.9%) rejected adequate teacher preparation. Twenty-four (88.9%) endorsed cost disparities. Overall, 26 (96.3%) rejected at least one of the three enabling conditions, and 14 (51.9%) rejected all three. Anticipated benefit and perceived implementation constraints therefore co-occurred within individuals. The remaining benefit endorser, S8, accepted those three conditions but endorsed cost disparities.

B. Teachers' Explanations

Coding identified access and affordability in 26 responses, equity-supportive potential in 14, institutional readiness or public provision in 11, and cultural or linguistic representation in 7. One response expressed uncertainty. Counts exceed 32 because codes could co-occur. The categories included both favourable and critical accounts.

Access accounts specified devices, reliable internet, subscription costs, and home learning environments. S1 rejected equal access and wrote that *"not all students have access to technology at home, so the divide begins there."* Others distinguished free access from more capable paid services. These accounts specify material differences underlying the access and cost ratings.

Of the 14 responses coded for equity-supportive potential, 12 came from participants endorsing personalized support and two from participants disagreeing with that item (S11 and S20). S20 wrote that AI could *"help level the playing field by giving students personalized support, translation tools, and extra help they might not get at home,"* while qualifying this potential with fair access and representation. Acknowledging possible benefits in writing did not always translate into agreement with the closed-ended statement.

Institutional accounts connected equitable use to funding, devices, subscriptions, guidance, and professional development. S5 endorsed personalized support but rejected adequate teacher preparation, explaining that *"the teacher needs to be able to use it adequately."* This response requested continuing professional development, policy documents, and examples, linking the preparation rating to specific forms of organizational support.

Cultural and linguistic accounts extended the ratings. S9 described English-language and Western orientations, while S24 emphasized free tools, multilingual use, and adaptability to different learners. S8 rated access, resources, and preparation positively but identified cultural bias in writing. These accounts indicate dimensions of equitable use beyond those directly measured by the five items.

IV. Discussion

Conditional equity connects an anticipated benefit with the conditions governing who can receive it. Fig. 1 organizes this interpretation across student, teacher, and institutional levels. Its arrows depict proposed dependencies derived from participants' accounts; the survey did not test causal pathways to equitable implementation.

Access and affordability, teacher preparation, and institutional provision intersected with cultural and linguistic responsiveness. This interpretation is consistent with work on infrastructure, educator readiness, and bias in inclusive AI [12], [13], and UNESCO's emphasis on policy and human-capacity development [14]. The linked accounts show how these conditions qualified participants' expectations, including cases where written explanations differed from item ratings.

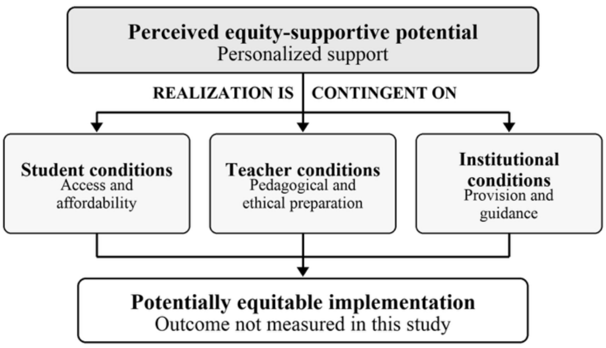

Fig. 1. Conditional equity as a conceptual interpretation. Arrows depict proposed dependencies; implementation outcomes were not measured.

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Teacher preparation has a specific implication for the course because it received the strongest negative rating. A systematic review found that research on classroom AI applications has outpaced work on teacher professional development [15]. Design-oriented work identifies scaffolding, output verification, bias awareness, and assessment design as relevant pedagogical priorities [7], [16]. Future course activities could ask graduate students to evaluate an AI-supported task for unequal access, output bias, and required teacher guidance, then revise it for their teaching context. This is a proposed response to the findings; its effects on professional learning remain to be evaluated.

For schools, participants' responses suggest examining access, affordability, and teacher support when planning AI provision. Planning should consider which functions are available at no cost, how students obtain reliable access, and how tools meet learners' linguistic and cultural needs. Whether these measures improve educational equity requires further investigation.

V. Limitations and Future Direction

The small convenience sample from one educational technology course limits transferability. Participants may differ from other educators in their interest in or experience with AI, although this was not measured. Findings represent their situated perceptions and cannot be generalized as population estimates.

Five adapted items and one open-ended question offer limited coverage of equitable AI use. The instrument was not validated as an equity scale, the forced-choice format excluded neutrality, and brief responses restricted qualitative depth. The course setting and 2% completion bonus, without an equivalent alternative, may have influenced participation or favourable responding.

Linked ratings and written explanations support a descriptive interpretation of conditional equity, but do not establish that any condition is causally necessary or sufficient. Differences between response types also limit their treatment as a single consistent participant profile. Implementation effects and student outcomes were not measured.

Future studies should use broader validated equity measures and examine whether course learning informs classroom decisions. Comparative school studies could connect perceived conditions with observed opportunities. Emerging agentic designs that integrate learner models, learning analytics, and proactive support [17] also warrant examination for how they alter these implementation conditions.

VI. Conclusion

This course-based SoTL inquiry identifies professional learning priorities arising from graduate students' expectations and judgments of equitable AI use. Conditional equity organizes those accounts by linking anticipated personalized support to access, preparation, and institutional provision. It offers a focus for course reflection and implementation planning whose usefulness requires evaluation beyond this sample.

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