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AI Policy in Higher Education: Relational-Affective Considerations for Governance in a Canadian University Case Study

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ABSTRACT

Generative artificial intelligence is reshaping higher education and raising new questions for policy, pedagogy, and governance, especially in STEM-related contexts. This mixed-methods case study examined faculty perceptions of the pedagogical, governance, and operational implications of AI at a Canadian university. Survey and focus group findings revealed limited current use, stronger anticipated future use, and widespread concerns about academic integrity, trust, workload, authenticity, and professional support. The analysis suggests that relational and affective conditions shape how AI policy is interpreted and enacted in academic practice. It further proposes that a relational-affective dimension may extend existing policy frameworks, particularly in STEM-oriented governance where technical judgement, accountability, and human oversight remain central.

Keywords: Generative artificial intelligence, higher education policy, mixed-methods case study, relational-affective dimension, STEM higher education

INTRODUCTION

The rapid emergence of generative artificial intelligence (AI) technologies has intensified debate about their role in higher education. Unless otherwise specified, AI here refers to generative systems such as ChatGPT, Claude, and Gemini that produce text, images, and audio and support decision-making. These affordances are disruptive and transformative, raising questions about preserving core values while embracing innovation (Chan & Colloton, 2024; Luckin, 2025; Selwyn, 2022). Miao et al. (2021) stress that policies must regulate AI while fostering equitable, ethical, and sustainable approaches. Frameworks must remain adaptive to evolving technologies and shifting expectations. Although much public and scholarly discussion has focused on humanities and social science teaching, generative AI is also rapidly reshaping STEM-related contexts. Examples include automated and AI-assisted support in engineering design and curriculum development (Mosly, 2024), diagnostic support in medical training (Zhang et al., 2024), and adaptive tools in mathematics education (Opesemowo & Ndlovu, 2024). These developments matter because AI in many STEM contexts intersects with simulation, modelling, professional judgement, and high-stakes decision-making. Policy debates would therefore benefit from engaging STEM explicitly, even where empirical comparisons across disciplinary categories remain limited. In STEM-related settings, AI introduces specific complexities concerning simulation reliability, the governance of clinical and educational data, algorithmic assessment, and the calibration of human judgment in relation to automated systems (Ahsan, 2025; Zhang et al., 2024). Technical fixes alone are unlikely to be sufficient. These challenges also raise relational and affective questions, including trust in collaborative work, uncertainty in AI-assisted reasoning, and the maintenance of accountable supervision. While the present study does not provide a formal comparative analysis across disciplines, it interprets faculty accounts in light of broader STEM-oriented debates and argues that relational and affective concerns warrant explicit attention in responsible policy formation.

Context and Problem Statement

Generative AI's integration into higher education has been met with ambivalence. Advocates highlight benefits such as automation of routine tasks, personalized feedback, and creative support (Kasneci et al., 2023; Moorhouse et al., 2023). Evidence shows AI can reduce workloads by generating materials and scaffolding student writing (Songkram et al., 2025). Critics caution that reliance on AI may erode competencies, reduce motivation, and hinder higher-order thinking (Bond et al., 2024). Institutions such as the University of British Columbia (2024) warn of threats to writing instruction and integrity, while others highlight inequities linked to unequal AI access (Chan & Lee, 2023; Crompton & Burke, 2023; Mah & Groß, 2024). AI systems are not socially neutral. Biases in training data disadvantage marginalized groups (Bender et al., 2021; Noble, 2018). Faculty worry that outputs reproduce stereotypes or exclude non-dominant knowledge systems, undermining diversity and inclusion (Knox, 2020). Without intervention, AI risks amplifying educational inequalities (Zawacki-Richter et al., 2019). In Canada, decentralized governance complicates consistent policy development (Berdahl, 2025). Universities also carry commitments to equity, diversity, and inclusion, alongside obligations to uphold Indigenous knowledge systems and data sovereignty (Truth and Reconciliation Commission of Canada, 2015). Indigenous scholars stress that AI may conflict with relational epistemologies privileging community and accountability (Smith, 2021). Imported global models risk neglecting Canadian contexts.

Some STEM-related disciplines add further complexity, balancing technical precision, ethics, and relational accountability. In fields such as biology, engineering, and medicine, AI policy may also need to account for lab integrity, sensitive data, competence, and trust. Read against the wider literature, these conditions suggest that relational-affective issues should be treated as relevant to STEM-oriented AI governance, particularly where technical judgement, supervision, and accountability are central. Policies that neglect these concerns risk overlooking the practices that sustain ethical science and interdisciplinary collaboration. Faculty perspectives remain underexplored. Recent studies suggest that many instructors remain uncertain about how to guide responsible AI use, redesign assessments, and interpret institutional expectations in practice (Baggia et al., 2026; Mah & Groß, 2024; Vivas-Urias et al., 2026). Qualitative studies document frustration and strain in enforcing integrity without guidance (Li & Zhang, 2025; Schiff, 2022). The gap between institutional aspirations and teaching realities underscores the need to ground AI governance in faculty experience. Without this grounding, policies risk disconnection from relational-affective realities of classrooms.

Purpose and Research Questions

Although research on AI in education is growing, faculty voices remain underrepresented. Much scholarship has prioritized student perspectives, institutional strategy, or broad policy discourse (Schiff, 2022). More recent work has begun to examine university teachers' perceptions, attitudes, and practices with generative AI, showing a pattern of guarded interest shaped by concerns about integrity, workload, ethics, and institutional support (Baggia et al., 2026; Vivas-Urias et al., 2026). Even so, limited attention has been paid to how faculty interpret policy, navigate tensions across disciplinary contexts, and articulate governance needs grounded in everyday teaching. This omission matters because faculty are central to policy enactment, assessment design, and the maintenance of institutional culture. This study applies Chan's (2023) AI Ecological Education

Policy Framework to a single-institution Canadian case and explores whether faculty accounts reveal issues not fully captured by the framework's pedagogical, governance, and operational dimensions. Particular attention is given to the relevance of these issues for STEM-oriented policy contexts, where questions of technical judgement, supervision, accountability, and collaboration are salient. In that context, the analysis examines the usefulness of a relational-affective dimension for interpreting concerns about trust, authenticity, and emotional labour in teaching and learning.

The study addresses the following research questions:

1. How do faculty at a Canadian university perceive the pedagogical, governance, and operational implications of AI in higher education?
2. What relational and affective considerations emerge in faculty accounts, and how do these extend existing policy frameworks, including for STEM-oriented contexts?
3. How might faculty perspectives from this institutional case inform equity-centred approaches to AI policy in higher education, particularly where technical judgement, accountability, and human oversight are central?

LITERATURE REVIEW

Academic Integrity and Governance

Generative AI complicates integrity frameworks that assume human authorship verified through text-matching (Bretag, 2019). AI outputs are novel and difficult to trace, limiting detection tools (Cotton et al., 2023). Policy responses have ranged from restrictive approaches to cautious experimentation with transparent use (Cavendish, 2023). Canadian institutions show similar variation, from prohibitions to selective integration (Plata et al., 2023). Governance extends beyond integrity to authorship, copyright, and data privacy. Faculty remain uncertain about how to cite AI content or whether attribution should resemble that for software or secondary sources (Foltynek et al., 2023). In Canada, governance also intersects with Indigenous data sovereignty (Truth and Reconciliation Commission of Canada, 2015). Without clear frameworks, faculty improvise, producing inconsistent enforcement and inequities (Azevedo et al., 2024; Schiff, 2022). Scholars argue governance must be adaptive, not only regulatory (An et al., 2025; Selwyn, 2022). Policies limited to prohibition risk fostering surveillance and mistrust while discouraging innovation (Dai et al., 2024). Recent work further argues that generative AI exposes weaknesses not only in student conduct regimes but in the wider integrity ecosystem of assessment design, policy coherence, and institutional culture; this supports a shift from narrow detection models toward systemic and educative approaches to integrity governance (Maleki, 2026).

Stakeholder Engagement and Communication

Policy effectiveness depends on both content and process. Engagement is critical for legitimacy (Bryson & Winfield, 2017; Miao et al., 2021), yet faculty are rarely consulted, fostering resistance and uneven uptake (Jin et al., 2025; Schiff, 2022). Students encounter inconsistent expectations across courses, leading to anxiety (Kasneci et al., 2023).

Clear communication mitigates these issues. Poorly worded or inconsistently shared policies generate "policy fatigue" (Eaton, 2023; Moore & Lookadoo, 2024). Students comply more readily when rules are explicit and tied to learning goals (Azevedo et al., 2024). Institutions should embed AI guidelines in orientation, syllabi, and training (Buele & Llerena-Aguirre, 2025).

Participatory design is widely recommended, with collaboration among faculty, students, and administrators (Bond et al., 2024; Eaton, 2023). Such models align with UNESCO's (2023) call for inclusive governance and draw on faculty expertise in pedagogy and assessment (Kizilcec, 2024).

Equity and Access

Equity is central to AI policy. Unequal access to tools across socio-economic groups risks widening digital divides (Chan & Lee, 2023; Crompton & Burke, 2023). Students with subscriptions or stronger connectivity gain advantages, while others are disadvantaged. Faculty note similar inequities undermining fairness (Mah & Groß, 2024).

AI systems also reproduce bias in training data (Gulson et al., 2022). Language models frequently generate stereotyped or exclusionary outputs (Bender et al., 2021; Noble, 2018). In Canada, these risks intersect with Indigenous concerns about cultural erasure and the devaluation of land-based knowledges (Smith, 2021).

Faculty equity is similarly uneven. Part-time and contract instructors face barriers to professional development due to workload and lack of support (Kahn et al., 2024; Macfarlane, 2011). Policies ignoring these conditions deepen inequities in AI readiness. UNESCO (2023) emphasizes that equity must be central to governance to avoid entrenching inequalities.

Frameworks for AI in Higher Education

Frameworks for AI in education commonly emphasize ethics, equity, and sustainability (Government of Canada, 2023; Miao et al., 2021; UNESCO, 2023). However, they often remain too abstract to guide institutional adaptation and do not sufficiently address the policy and sociotechnical conditions shaping digital education in the AI era (Dai et al., 2024; Selwyn et al., 2026). Chan's (2023) framework identifies three interrelated dimensions: pedagogical, governance, and operational. The pedagogical dimension concerns teaching practice; governance addresses regulation and integrity; and the operational dimension focuses on professional development and infrastructure. The framework also stresses the interdependence of these dimensions.

Faculty experiences may suggest that existing frameworks do not fully account for relational-affective dynamics. Recent scholarship likewise indicates that institutional capacity depends on how faculty competencies are conceptualized and supported. A generative AI-responsive competency framework for university teachers identifies four interrelated areas requiring development: GenAI literacy, curriculum and learning design, teaching and learning, and assessment (Sun et al., 2026). This work can complement policy-oriented frameworks by clarifying the pedagogical and operational capacities that institutions must build for faculty to integrate AI responsibly and critically. Faculty accounts in emerging higher education research, including the present study, highlight trust, authenticity, and emotional labour as important considerations for AI adoption and governance. These concerns are consistent with scholarship showing that technologies are socially and emotionally embedded (Knox, 2020), and with emerging research indicating that trust is a central condition shaping perceptions of and willingness to adopt AI-powered educational technologies (Nazaretsky et al., 2025). Considering a relational-affective dimension may make these conditions more analytically visible and may better capture how accountability, trust, and affective workload shape AI practice in institutional settings, including STEM-related environments where technical performance and human oversight are closely intertwined.

RESEARCH METHOD

This study employed a mixed-methods case study design to examine faculty perceptions of AI in higher education at a single Canadian university, combining quantitative and qualitative data to develop both descriptive breadth and interpretive depth (Creswell & Plano Clark, 2023). The study is institutionally bounded, but it was designed in relation to policy questions that are especially pressing in STEM-related settings, including assessment integrity, technical judgement, supervision, and accountability. An explanatory sequential logic guided the design. Survey data were collected and analyzed first in order to identify broad patterns in faculty perceptions and priorities. Focus groups were then conducted to elaborate, contextualize, and interpret those survey patterns in greater depth (Schoonenboom & Johnson, 2017). The two strands were analyzed separately before being brought together in the discussion of integrated findings.

Participants

Participants were recruited from full-time and part-time faculty at Mount Saint Vincent University. A purposive strategy ensured disciplinary and experience diversity. Of 350 invited faculty (150 full-time, 200 part-time), 53 completed the survey, a response rate of 15 percent. The survey was open for four weeks in February 2025, following ethics approval in January. Recruitment involved an internal faculty-wide email list and the Teaching and Learning Centre newsletter. To maximize reach, an announcement was circulated one week prior to launch, and two reminders were sent. Faculty could enter a draw for one of four $50 gift cards. Three focus groups complemented survey findings. Groups were stratified by contract status: one with five full-time faculty, one with four part-time faculty, and one with three mixed-status participants. Group size ranged from three to five. Across the three groups, participants represented a mix of disciplinary backgrounds, including STEM-related and non-STEM fields. This breadth is useful for interpreting institutional policy questions with relevance across higher education, including STEM contexts. However, because the focus groups were organized by contract status rather than discipline, the study does not support systematic comparison between disciplinary categories.

Instruments

The survey adapted prior research on AI policy frameworks to the Canadian context (Chan, 2023), with added items on training needs. It included demographics, Likert-scale items on AI attitudes, multiple-choice questions on AI use, and open-ended concerns and recommendations. A pilot with five faculty members improved clarity. Survey domains were demographics, AI familiarity and use, perceptions of teaching impact, perceived effects on higher education, professional development needs, and policy recommendations. This paper reports results on faculty perceptions, perceived implications of AI for teaching and higher education, and policy-related guidance. The focus groups followed a semi-structured protocol covering five domains: AI usage; teaching impact; pedagogy; institutional support; and future perspectives. Questions elicited experiences, strategies for integrity, and expectations for governance. Probes encouraged elaboration. Discussions were transcribed verbatim.

Data Collection

Ethics approval was obtained in January 2025. The online survey, administered via LimeSurvey, required 20–30 minutes. Participants consented electronically. The survey was open for four weeks with two reminders. Some participants hesitated to record sensitive views on integrity, which may have influenced responses.

Focus groups were conducted after the survey. Each lasted 60–75 minutes and was moderated by a trained facilitator. Notes were taken to support transcription.

Data Analysis

Survey data were analyzed using descriptive statistics, including frequencies, means, medians, and standard deviations, in SPSS (Version 29). Qualitative data from survey comments and focus groups were analyzed through Braun and Clarke's (2006) six-phase thematic analysis, supported by MAXQDA. Survey comments were openly coded, then refined into themes.

For the focus groups, two researchers first read one transcript independently and compared their preliminary coding to refine category definitions, resolve ambiguities, and strengthen analytic consistency. This process was used to support interpretive rigour rather than to calculate coding reliability in a positivist sense. The remaining transcripts were then coded using the refined analytic scheme, with ongoing discussion between the researchers as themes were consolidated. Themes were subsequently mapped onto four analytic dimensions, pedagogical, governance, operational, and relational-affective, in order to support systematic comparison across the data set.

Integration followed the explanatory sequential design by bringing survey patterns and qualitative themes into dialogue during interpretation. Quantitative findings identified broad areas of concern and anticipated change, whereas qualitative data clarified, contextualized, and complicated those patterns. Convergence, complementarity, and points of tension were identified through interpretive comparison across the two strands.

RESULTS

Faculty expressed a combination of caution, ethical concern, and curiosity regarding the integration of generative AI. Current use was limited, yet there was broad anticipation of future adoption, provided institutional support and guidance are strengthened. Because this study employed an explanatory sequential mixed-methods design, quantitative and qualitative results are reported together. Survey findings provide descriptive patterns, while focus group transcripts and open-ended responses offer elaboration. Presenting both strands thematically provides a more integrated account of faculty perspectives. Interpretation of the results involved comparing descriptive survey patterns with qualitative accounts to identify convergence, complementarity, and points of tension between the two strands. Appendix A reports descriptive statistics for all 33 survey items, including the full item wording.

Awareness and Anticipated Use

Descriptive analysis of 33 Likert items indicated low current engagement with generative artificial intelligence. Personal use was below the scale midpoint ($M = 2.36$, $SD = 1.13$), as were teaching use ($M = 2.15$, $SD = 1.17$) and research use ($M = 1.75$, $SD = 1.05$). Anticipated future integration in teaching was higher ($M = 3.43$, $SD = 1.55$). Open responses and focus group data illustrated pragmatic anticipation coupled with a desire for responsible uptake. For example, one participant stated, “Students will use it, so it’s a matter of how to use it responsibly and efficiently.” Another indicated a procedural approach to disclosure and monitoring: “I ask them to submit a file that includes an acknowledgment of their AI use. If they did use AI, then they need to include the prompts and the output.”

Optimism and Ethical Concerns

Perceptions reflected a mix of instrumental optimism and ethical caution. Respondents agreed that students should learn to use AI for career preparation (M = 3.53, SD = 1.23). They also expressed moderate agreement that AI may provide students with unique insights and perspectives (M = 3.51, SD = 1.38), that students may ask AI questions they might hesitate to ask a teacher (M = 3.75, SD = 1.19), and that students may feel less judged when interacting with such tools (M = 3.68, SD = 1.17). At the same time, respondents were concerned that AI use in assignments could create an imbalance by giving some students an advantage over others (M = 3.72, SD = 1.34). Open responses captured this ambivalence. One respondent wrote, “On an ethical level, it is extremely concerning. On a productivity level, it is amazing. The key is balance.” Another cautioned, “I am massively concerned. It is a powerful technology that is not yet a reliable tool.” Others emphasized the need for human presence and whole-person education, noting that interpersonal dimensions of learning cannot be replicated by AI.

Attribution and Academic Integrity

Support for acknowledgement requirements was strong across qualitative responses. Participants consistently advocated explicit citation or signed declarations of use. Examples included, “Yes, students should be required to include a signed statement of AI usage at the end of each assignment,” and “Absolutely necessary. The ideas are not their own. Credit must be given.” Others advocated course-level prohibition or in-person verification. As one respondent explained, “I do not allow students to use AI in any capacity. In-person testing assures me the work is theirs.” Faculty also described practical verification strategies, including comparing in-class writing with take-home submissions and holding individual meetings to resolve discrepancies. Some respondents highlighted the burden created by large volumes of suspected cases and uncertainty about proof thresholds.

Professional Development Needs

Survey items indicated substantial demand for professional development in several areas. Respondents reported a need for training on detecting and addressing algorithmic bias in generative AI tools (M = 3.74, SD = 1.37), institutional support to understand the ethical implications of AI use in teaching and learning (M = 3.58, SD = 1.20), and guidance on incorporating AI into assessment while maintaining academic integrity (M = 3.60, SD = 1.32). There was also demand for workshops on designing AI-inclusive curriculum strategies (M = 3.43, SD = 1.37). Respondents sought both conceptual grounding and practical strategies. Illustrative comments included, “Provide professional development on authenticity, bias, hallucinations, and security, not only tips and tricks,” and “Offering concrete examples on how AI can be used for designing teaching materials, assignments, and exams.” Several respondents requested discipline-specific sessions and accessible formats for part-time faculty, such as recordings and modular offerings. A minority expressed little interest in training, viewing AI as a background tool that will normalize over time. This pattern is consistent with recent higher education research indicating that faculty readiness depends not simply on exposure to tools, but on structured support for pedagogical adaptation, assessment redesign, and critical understanding of AI’s institutional implications (Sun et al., 2026; Vivas-Urias et al., 2026).

Pedagogical Shifts and Assessment Redesign

Participants reported adjustments to task design and evaluation to preserve authenticity and higher-order learning. Many described a shift toward invigilated assessments, oral components, multimodal deliverables, scaffolded projects, and process evidence. Examples included, “I have moved back to in-person assessments and added oral components,” and “I use presentations, posters, and process evidence such as appendices and edit histories to verify learning.” Others emphasized alignment with course materials and lived experience to reduce generic responses. Some respondents framed AI as a legitimate scaffold that must be paired with critique, authorship, and responsibility. One noted, “I think this can be a scaffolding tool, but ultimately authorship and responsibility remain with the student. ChatGPT is no more an author than SPSS or MAXQDA.”

Institutional Support and Governance

Quantitative items indicated strong agreement that institutions should have policies and strategies for managing AI integration (M = 4.72, SD = 0.57). Open responses emphasized system-level responsibilities for coherence, workload, and due process. One respondent stated, “University administrations need to take this seriously. Responsibility for preventing improper use should not fall solely on individual faculty.” Others asked for course outline language on acceptable uses, intellectual property guidance, and streamlined integrity procedures. Requests for professional development extended to policy communication and equity of access, with attention to the constraints facing part-time instructors.

Relational-Affective Considerations

Participants described heightened anxiety, frustration, and demoralization associated with detection challenges, inconsistent norms across courses, and concerns about the erosion of authentic engagement. Comments included, "I think a lot needs to be learned and a better understanding among faculty. I am open to my students using AI, but they may go to another course where it is not allowed so we start to create conflicting messages," and "Dealing with students who use AI even though it has been forbidden, and trying to set up meaningful assignments that avoid student use of AI is exhausting." Several respondents requested recognition of the added emotional and temporal load and suggested institutional mechanisms that reduce individual exposure to adversarial interactions.

Integrated Summary of Findings

Across the survey findings and qualitative accounts, a broadly consistent pattern emerged. Current faculty use of generative AI was limited, whereas anticipated future use was notably higher when institutional supports and clearer guidance were assumed. The strongest consensus concerned the need for institutional planning and governance. Perceived benefits included students' access to immediate assistance, opportunities for hesitant questioning, some enhancement of digital competence, and exposure to unfamiliar perspectives. At the same time, respondents expressed concern about writing, social interaction, fairness, trust, and over-reliance. Professional development priorities centred on ethics, bias, assessment design, and discipline-specific implementation. Against that backdrop, faculty perspectives appear less as simple acceptance or rejection than as an attempt to negotiate pedagogical opportunity amid governance uncertainty, operational strain, and relational concern.

DISCUSSION & CONCLUSIONS

Discussion

Faculty in this Canadian single-institution case study approached generative artificial intelligence with guarded interest and unease, in ways that carry wider relevance for STEM-oriented policy discussions as well as for higher education governance more broadly. Survey responses and qualitative accounts pointed in a similar direction. Present use remained relatively modest, yet many participants anticipated broader uptake if institutions provided clearer policies, stronger pedagogical support, and more credible professional development. The findings reflect more than caution about a novel tool. Rather, generative AI seems to intensify older tensions within higher education concerning authorship, fairness, trust, workload, and the purposes of assessment itself.

In relation to prior scholarship, this pattern is recognizable. A growing body of international research has documented a tension between the administrative and pedagogical efficiencies associated with generative AI and persistent doubts about reliability, educational value, and ethical legitimacy (Kasneci et al., 2023; Moorhouse et al., 2023). Faculty in the present study described much the same problem, though often in more grounded terms. AI could help with procedural tasks, idea generation, or limited forms of instructional support; yet those same affordances raised concern about shallow engagement, displaced judgement, and the weakening of student authorship. For many participants, efficiency did not appear to be the central criterion. Educational worth remained the harder question.

Academic integrity concerns extended well beyond a narrow concern with misconduct. Existing institutional models, especially those built around text-matching and conventional proof standards, were widely perceived as ill-suited to generative outputs or AI-assisted work (Bretag, 2019; Cotton et al., 2023). What faculty described was less a single enforcement problem than an unsettled authorship regime. Acknowledgement protocols, signed declarations, oral verification, and process documentation were often proposed because conventional markers of originality no longer seemed sufficient. Recent work on integrity ecosystems is useful here; the challenge is not simply whether one can detect prohibited use, but whether assessment design, institutional communication, and policy culture remain coherent under altered production conditions (Azevedo et al., 2024; Eaton, 2023; Maleki, 2026). That pressure was evident throughout the data.

Questions of equity and access were also important. Participants worried about the uneven distribution of subscription-based tools, disparities in digital fluency, and the possibility that AI-assisted work may advantage students already positioned more favourably within academic systems. These concerns align with scholarship showing that algorithmic systems can reproduce and, at times, amplify existing inequalities (Bender et al., 2021; Noble, 2018). Within the Canadian context, the matter takes on additional complexity because institutional commitments to equity, diversity, and inclusion intersect with obligations regarding Indigenous knowledge, sovereignty, and relational accountability (Smith, 2021; Truth and Reconciliation Commission of Canada, 2015). Imported models of AI governance may miss important local conditions. Faculty concerns suggest that policy cannot be framed simply as technological adaptation; it is also an issue of epistemic responsibility and institutional justice.

Professional development emerged as another major site of tension. Participants did not merely ask for technical instruction on how to use tools. More often, they identified a need for conceptual grounding, discipline-sensitive exemplars, and practical support for redesigning assessment, addressing algorithmic bias, and interpreting policy expectations in ordinary teaching contexts. Recent literature similarly argues that faculty readiness depends on structured support for curriculum adaptation, assessment redesign, and a critical understanding of AI's institutional implications, rather than on casual exposure to platforms or tipsheets (Bond et al., 2024; Kizilcec, 2024; Sun et al., 2026; Vivas-Urias et al., 2026). Some respondents also stressed the uneven labour conditions under which such development occurs, particularly for part-time instructors. This point is consequential for policy design. Operational readiness is inseparable from institutional arrangements of time, compensation, and recognition.

Less often foregrounded in some policy discourse, relational and affective pressures were especially pronounced in these data. Faculty described frustration, anxiety, demoralization, and a sense of relational erosion when trying to judge authorship, maintain trust, or manage inconsistent norms across courses. Research on teacher emotion has long shown that professional strain intensifies when educators experience threats to pedagogical values, self-understanding, or relational integrity, and that emotional labour may contribute to burnout under such conditions (Bodenheimer & Shuster, 2020; Hargreaves, 2000; Kariou et al., 2021; Kelchtermans, 2005). This interpretation is also consistent with broader work in teacher emotion research that treats affect as integral rather than incidental to professional practice and judgement (Schutz & Zembylas, 2009). The present study suggests that generative AI may sharpen those conditions. Across participant accounts, trust, authentic engagement, and relational accountability were linked to the practical viability of AI policy, with clear relevance for STEM-oriented contexts where supervision, accountability, and professional judgement are central. These concerns should not be treated as secondary matters. They appeared to shape how governance was experienced, resisted, or rendered workable.

Chan's (2023) AI Ecological Education Policy Framework remains a valuable starting point, particularly in its attention to pedagogical, governance, and operational dimensions. Even so, faculty accounts in this study suggest that these dimensions may not fully capture the lived conditions under which policy is interpreted and enacted. Trust, emotional labour, authenticity, and relational accountability appeared in the data as recurring concerns rather than incidental effects. On that basis, the study supports considering a relational-affective dimension as a useful analytic extension. This point is especially important for STEM-oriented policy contexts, where technical performance, supervision, and accountable judgement are often treated as primary concerns even though they are enacted through human relationships, trust, and oversight. The claim should nevertheless be understood with appropriate caution: the present findings arise from a single institutional case and do not establish a definitive framework revision across disciplinary or national contexts.

Implications for Policy and Practice

Viewed in these terms, consideration of a relational-affective dimension does not simply refine the framework conceptually; it also has implications for how institutions might approach assessment, governance, professional development, and student support, including in STEM-related environments where verification, safety, and professional accountability remain central.

Pedagogically, the findings support treating assessment redesign as a systemic priority rather than an individual instructor adaptation. Participants described movement toward oral examinations, scaffolded assignments, multimodal tasks, in-class work, and process evidence such as appendices, edit histories, or reflective commentary. These strategies were not framed as perfect solutions. They were seen instead as ways of re-establishing visibility into student thinking and preserving higher-order engagement where AI can generate polished but detached outputs. Critical AI literacy could also be embedded at the programme level. Students need support not only in using tools but in interrogating hallucinated references, normative assumptions, shallow synthesis, and the limits of machine-generated text. A hybrid model, in which some tasks permit responsible AI use and others remain AI-independent, appeared more educationally defensible than either blanket prohibition or unrestricted integration.

The findings point to the need for greater consistency, clarity, and participatory design. Faculty were often less concerned with whether rules were strict than with whether they were coherent across institutional settings. Uneven expectations create confusion for students and place disproportionate interpretive burdens on instructors. Transparent attribution protocols, common baseline policy language, and mechanisms for disciplinary adaptation would therefore be important. Participatory structures matter as well. Standing committees or consultative groups involving faculty, students, staff, and relevant administrative units would likely improve legitimacy and responsiveness, especially where policy is evolving rapidly. A solely top-down approach risks producing procedural compliance without pedagogical credibility.

Operational implications centre on the distribution of institutional support. Variation in prior knowledge, confidence, and workload suggests the need for tiered professional development pathways rather than one standardized model. Asynchronous and modular formats are especially important where part-time faculty or precariously employed instructors face limited access to paid development opportunities. Participants also indicated that training should include mental health awareness, case management guidance, and escalation pathways for suspected misuse. Participants described not only a skills deficit but also a broader deficit in institutional support.

The relational-affective implications deserve explicit policy recognition. Integrity monitoring, repeated adjudication of suspected misuse, and the need to navigate inconsistent norms all generate substantial hidden labour. Institutions rarely count that work clearly. Co-created AI agreements with students may help preserve trust while clarifying expectations, especially in courses where reflective, experiential, or personally situated writing remains central. Educative and non-punitive responses were also preferred by many participants, not because misconduct is inconsequential, but because adversarial enforcement alone may heighten anxiety without improving understanding or ethical judgment. These implications are summarized in Table 1.

Table 1

Policy Implications for AI in Higher Education

Dimension	Faculty concerns	Policy recommendations
Pedagogical	Efficiency versus deep learning; reduced authenticity; erosion of foundational skills	Redesign assessments for higher-order skills, including oral, multimodal, and scaffolded formats; embed programme-level AI literacy outcomes; balance AI-enabled and AI-independent tasks.
Governance	Inconsistent policies; lack of clarity; equity risks	Standardise attribution protocols; establish baseline policies with equity audits; use participatory policy design through standing committees, including faculty, staff, and students
Operational	Uneven readiness; limited access for part-time faculty; stress from enforcement	Provide tiered training pathways with certification; offer asynchronous and modular programming with compensation; include trauma-informed and peer-support mechanisms.
Relational-affective	Increased emotional labour; declining trust; student anxiety	Recognise AI monitoring in faculty workloads; co-create AI agreements with students; prioritise educative, non-punitive sanctions

Note. The table synthesizes faculty concerns and corresponding institutional responses derived from the integrated analysis of survey and focus group data.

STEM-related contexts warrant separate consideration because relational and affective pressures may intersect there with technical and operational demands in especially visible ways. In laboratory, engineering, and medical education, teaching and supervision often depend on teamwork, calibrated trust, accountable judgement, and responsible oversight under conditions where simulation, modelling, or AI-assisted decision support may carry high stakes. Research in medical and engineering education has already underscored these tensions, especially around diagnostic support, simulation reliability, implementation challenges, and the opacity of AI-mediated systems (Ahsan, 2025; Chan & Zary, 2019; Mosly, 2024; Zhang et al., 2024). The faculty concerns identified here, particularly those involving trust, authenticity, workload, uncertainty, and oversight, are relevant to STEM-oriented policy environments and support treating relational-affective conditions as a substantive rather than incidental concern in AI governance.

Integrity in laboratory and collaborative work is one such area. Generative tools may obscure individual contribution, simulate competence, or complicate judgements about authorship, thereby increasing the burden on instructors charged with verifying learning. Policies that require auditable prompt histories, model versions, and revision trails, alongside reflective authorship statements, may help restore procedural transparency. Trust in AI-assisted simulations and decision support is another. Over-reliance on opaque systems can distort judgement, especially where students are still developing disciplinary reasoning. Studies on human-AI collaboration suggest that decision-control mechanisms, cognitive-forcing prompts, and verification routines can reduce over-reliance more effectively than generic explanations alone (Buçinca et al., 2021; Westphal et al., 2023). Emotional labour may also become especially salient in high-stakes STEM settings where supervision, uncertainty, and safety concerns converge. Affect-aware professional development, explicit communication about model limits, and documented oversight protocols are therefore warranted. Finally, technical accuracy cannot be separated neatly from relational accountability. Work in epistemic cultures and collaborative evaluation suggests that credibility depends not only on correct outputs but also on the quality of justification, coordination, trust calibration, and an accountable process (Bozkurt & Sharma, 2024; Cetina, 1999; Fragiadakis et al., 2024; Latour & Woolgar, 2013).

Table 2 presents STEM-related implications as policy-relevant interpretive extensions informed by the broader framework, the study findings, and the surrounding literature, while retaining the argument that technical precision and relational conditions often remain intertwined.

Table 2

Policy Implications for STEM Contexts of AI Integration

Focus area	Faculty concerns and challenges	Policy recommendations
Integrity in laboratory and collaborative work	AI can obscure authorship, simulate competence, and increase emotional labour for instructors verifying contributions.	Require auditable histories of prompts, model versions, and edits; mandate reflective authorship statements distinguishing human and AI contributions.
Trust in AI-assisted simulations and decision support	Students may over-rely on opaque AI systems in modelling, diagnostics, or simulation-based work.	Integrate model literacy with decision protocols; introduce verification and counterfactual testing; design deliberative practices that reconcile AI outputs with disciplinary knowledge.
Emotional labour in high-stakes STEM settings	Faculty face heightened stress in clinical or engineering contexts; students experience anxiety; supervision demands intensify.	Provide affect-aware professional development; train faculty on communicating uncertainty, managing error escalation, and documenting oversight.
Interdependence of technical accuracy and relational accountability	Technical validation alone is insufficient; credibility depends on trust, coordination, and accountability	Pair accuracy metrics with process measures such as justification quality, team coordination, and trust calibration, embed relational practices such as peer challenge routines, and decision logs.

Note. The table summarises STEM-specific implications derived from the broader four-dimensional framework and supported by the interdisciplinary literature cited in the surrounding text.

LIMITATIONS AND FUTURE RESEARCH

Interpretation of these contributions requires some caution. The study was conducted at a single Canadian university and focused exclusively on faculty perspectives, which limits the generalizability of the analysis across the sector. Despite targeted recruitment, the survey response rate remained 15 percent. Self-selection is therefore a plausible concern, particularly if faculty with stronger views about AI or greater institutional engagement were more likely to participate. Such constraints do not nullify the value of the findings, but they do narrow the claims that can be made about representativeness. The qualitative component presents further limits. Focus groups were small and organized by contract status rather than by disciplinary breadth, which limited more systematic comparisons across fields. Although participants came from varied disciplinary backgrounds, including STEM-related fields, the study was not designed or powered to support robust comparisons between disciplinary categories. The relevance of the findings for STEM contexts should therefore be understood as interpretive and policy-oriented rather than as a direct empirical comparison. Group dynamics may also have shaped what participants were willing to disclose, especially on sensitive questions involving academic integrity, institutional uncertainty, or professional vulnerability (Krueger & Casey, 2015). As with most self-report studies, recall bias and social desirability effects cannot be ruled out.

At the same time, the explanatory sequential mixed-methods design strengthened the analysis by allowing triangulation across descriptive survey results, open-ended comments, and focus group discussions (Creswell & Plano Clark, 2023). Integration of the two strands added interpretive depth and made it possible to identify not only convergence, but also areas of tension or divergence. That breadth is useful, even if institutional scope remains narrow. Several directions for future inquiry follow. Multi-institutional research across different Canadian settings would help test the portability of the relational-affective dimension proposed here, particularly in research-intensive universities, polytechnic institutions, francophone settings, and contexts serving distinct regional or Indigenous communities. Comparative work across national systems would also be valuable because governance arrangements differ substantially. Canada's decentralized system, together with its policy commitments around equity and Indigenous sovereignty, may generate patterns that do not map neatly onto more centralized or market-driven systems (Crompton & Burke, 2023; Dai et al., 2024).

Longitudinal and ethnographic work would be especially helpful. Generative AI is evolving rapidly, and faculty perceptions are likely to shift as tools mature, institutional norms stabilize, and practical routines sediment. Concerns that presently dominate, such as detection or attribution, may diminish in salience while questions of intellectual property, multimodal authorship, infrastructural dependence, or automated feedback become more prominent. Iterative designs are needed if research is to track those changes with sufficient sensitivity (Chan & Hu, 2023; Holmes et al., 2019; Luckin, 2025). Further inquiry should also extend beyond the faculty. Students, educational developers, librarians, administrators, and academic integrity staff all shape how AI policy is interpreted and enacted. A broader stakeholder base would allow researchers to examine where understandings align, where they fracture, and how relational-affective concerns circulate differently across institutional roles. That wider lens may alter the framework again.

CONCLUSION

Generative AI appears unlikely to remain marginal in higher education, but the terms of its integration remain contested. In this single-institution Canadian case study, faculty recognized potential benefits in efficiency, support, and selected pedagogical uses, while also expressing sustained concern about equity, academic integrity, authenticity, workload, trust, and the weakening of educational relationships. The findings indicate that policy responses that focus solely on technical implementation or rule enforcement are likely to overlook important aspects of how AI is experienced in academic practice.

The study suggests that Chan's (2023) AI Ecological Education Policy Framework may be strengthened by explicitly attending to relational and affective conditions. Pedagogical redesign, governance clarity, and operational support remain necessary, but the data also point to trust, emotional labour, and relational accountability as recurring concerns in faculty experience. This argument has particular relevance for STEM-oriented policy contexts, where technical judgement, supervision, verification, and accountable oversight are often treated as primary concerns, yet are inseparable from the human relationships through which they are enacted. On that basis, a relational-affective dimension is best understood here as a useful analytic extension that may sharpen policy thinking in STEM as well as in higher education more broadly.

These conclusions should be interpreted with caution. The evidence derives from a single university and does not establish robust comparisons across disciplinary categories or the Canadian sector more broadly. Even so, the case provides a grounded basis for arguing that AI policy in higher education, including in STEM-related environments, should attend not only to what these technologies can do, but also to the conditions under which faculty and students are expected to exercise judgement, responsibility, and trust.

AI Usage Disclaimer

AI tools were used for limited editorial support during the final stages of manuscript preparation, including language clarity and stylistic consistency. No GenAI tools were used in data analysis, interpretation, or the development of substantive arguments. The authors retain full responsibility for all content and claims.

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Appendix A

Descriptive Statistics for Faculty Survey Items on Generative AI (N = 53)

Item	M	Mdn	SD
I have used Generative AI technologies for personal use.	2.36	2	1.13
I have used Generative AI technologies for teaching use.	2.15	2	1.17
I have used Generative AI technologies for research use.	1.75	1	1.05
I think the integration of Generative AI technologies in higher education will have a positive impact on teaching and learning in the long run.	2.92	3	1.38
I believe higher education institutions should have a plan in place for managing the potential risks associated with using Generative AI technologies in teaching and learning.	4.72	5	0.57
I envision integrating Generative AI technologies into my teaching and learning practices in the future.	3.43	4	1.55
I am concerned that the use of Generative AI technologies in assignments could create an imbalance, potentially giving some students an advantage over others.	3.72	4	1.34
I think Generative AI technologies will replace teachers in the future.	2.26	2	1.37
I believe students must learn how to use Generative AI technologies well for their career.	3.53	4	1.23
I think teachers can already accurately identify students' usage of Generative AI technologies to partially complete an assignment.	2.87	3	1.44
I believe Generative AI technologies can provide guidance for coursework as effectively as human teachers.	2.23	2	1.30
I think using Generative AI technologies to complete assignments undermines the value of a university education.	4.04	5	1.27
I believe students can ask questions to Generative AI technologies that they might otherwise hesitate to express to their teacher.	3.75	4	1.19
I think students will not feel judged by Generative AI technologies such as ChatGPT, so they feel comfortable with it.	3.68	4	1.17

I believe Generative AI technologies will limit students' opportunities to interact with others and socialize while completing coursework.	3.83	4	1.27
I think Generative AI technologies will hinder students' development of generic or transferable skills such as teamwork, problem-solving, and leadership skills.	3.83	4	1.41
If a fully online programme with the assistance of a personalized Generative AI tutor was available, I believe students should be open to pursuing their degree through this option.	2.74	3	1.64
I am concerned that students can become over-reliant on Generative AI technologies for their work or studies.	4.36	5	0.98
I believe Generative AI technologies can improve students' digital competence (combination of knowledge, skills, and attitudes necessary to critically and responsibly use digital technologies).	3.30	3	1.32
I believe Generative AI technologies can improve students' overall academic performance.	3.19	3	1.44
I believe Generative AI technologies can help students save time.	3.70	4	1.14
I think Generative AI technologies can help students become a better writers.	2.87	3	1.52
I believe Generative AI technologies can provide students with unique insights and perspectives that they may not have thought of themselves.	3.51	4	1.38
I think Generative AI technologies can provide students with personalized and immediate feedback and suggestions for their assignments.	3.45	4	1.20
I think Generative AI technologies are a great tool for students as it is available 24/7.	2.98	3	1.35
I think Generative AI technologies are a great tool for student support services due to anonymity.	2.96	3	1.34
I require training on how to incorporate Generative AI technologies into assessments while maintaining academic integrity.	3.60	4	1.32
I need institutional support to understand the ethical implications of using Generative AI in teaching and learning.	3.58	4	1.20
I would benefit from workshops on designing Generative AI-inclusive curriculum strategies.	3.43	4	1.37

I need access to case studies or examples of best practices for integrating Generative AI in higher education.	3.62	4	1.33
Training on detecting and addressing algorithmic bias in Generative AI tools is essential for my teaching role.	3.74	4	1.37
I feel prepared to guide students on how to use Generative AI responsibly in academic work.	2.49	2	1.31
I need technical support or resources to experiment with Generative AI tools before integrating them into my teaching.	3.23	3	1.38

Note. M = mean; Mdn = median; SD = standard deviation.