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AI-Augmented Feedback in Online Graduate Courses: Impacts on Writing Self-Efficacy, Integrity Perceptions, and Equity

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The dissertation is submitted in partial fulfillment of the requirements for the degree listed above. The work presented is my own, and any assistance or sources are acknowledged in accordance with university regulations.

Abstract

The dissertation examines how structured use of generative AI (GenAI) tools as feedback partners in online graduate courses influences students’ writing self-efficacy, perceptions of academic integrity, and experiences of equity. Anchored in self-regulated learning, feedback literacy, and cognitive load theory, the study uses an explanatory sequential mixed-methods design. In the quantitative phase, students in AI-augmented writing-intensive courses are compared with peers in business-as-usual sections on standardized measures of writing self-efficacy, perceived workload, and integrity-related attitudes. In the qualitative phase, interviews and focus groups probe how students and instructors experience GenAI-supported feedback cycles, including disclosure practices and concerns about fairness. It is hypothesized that when GenAI is positioned as a critique and planning tool—rather than as a ghostwriter—students' self-efficacy and feedback-use behaviors improve without undermining perceptions of integrity. The study also explores distributional effects across equity-relevant subgroups such as first-generation status, language background, and disability accommodations. Findings aim to inform course and policy design by specifying conditions under which AI-augmented feedback supports learning, preserves authorship, and narrows rather than widens achievement gaps.

Chapter 1: Introduction

1.1 Context and Rationale

Since late 2022, generative AI tools capable of producing fluent academic prose have become widely accessible. Online graduate students—often balancing employment, caregiving, and study—are especially likely to adopt such tools for efficiency and on-demand support. Universities, however, face a complex challenge: they must safeguard academic integrity while also recognizing that appropriate uses of GenAI can scaffold writing development, particularly for students who receive limited human feedback (Kasneci et al., 2023; UNESCO, 2023). Blanket prohibition is increasingly impractical; yet unstructured use risks overreliance, hallucinated content, and inequities in access and literacy (OECD, 2024).

1.2 Problem Statement

Empirical evidence on GenAI in higher education writing is growing but remains fragmented. Many studies focus on performance improvements or detection accuracy in isolation, rather than modeling how AI-augmented feedback interacts with self-regulated learning and perceptions of fairness (Lee, 2024; Qi et al., 2025). There is limited research on online graduate contexts, where students are more heterogeneous and institutional support varies widely. Without integrated evidence, course designers and policy makers lack guidance on how to harness GenAI to improve feedback while preserving confidence in what grades represent.

1.3 Research Aims and Questions

The dissertation aims to develop and evaluate a structured model of AI-augmented feedback for online graduate writing. The study addresses three overarching questions:

1. Does participation in AI-augmented writing cycles increase students' writing self-efficacy relative to business-as-usual instruction?

2. How does AI-augmented feedback influence students' perceptions of academic integrity and fairness in assessment?

3. Do impacts differ across equity-relevant subgroups, and what mechanisms explain any differences?

1.4 Significance

Theoretically, the study links self-regulated learning, feedback literacy, and cognitive load perspectives to contemporary GenAI practice. Practically, it offers design principles for online graduate programs seeking to move beyond prohibition-versus-permission debates toward evidence-informed, equity-attentive implementation (UNESCO, 2023; OECD, 2024).

Chapter 2: Literature Review

2.1 GenAI and Academic Writing

Early commentary portrayed GenAI as both opportunity and threat: a potential tutor for idea development and revision, and a shortcut that could erode disciplinary thinking (Kasneci et al., 2023). More recent empirical work finds that when GenAI is used to critique drafts, suggest alternative structures, and generate targeted feedback aligned with rubric criteria, students often show gains in engagement, confidence, and writing quality (Meyer et al., 2024; Kinder et al., 2025). These benefits are strongest when tools are embedded in structured workflows that require students to plan prompts, cross-check suggestions, and document how feedback informed revision.

2.2 Self-Regulated Learning and Feedback Literacy

Self-regulated learning (SRL) frameworks emphasize cycles of planning, monitoring, and reflection in academic tasks (Zimmerman, 2002). Feedback literacy describes students' capacity to seek, interpret, and act on feedback (Carless & Boud, 2018). Studies indicate that SRL and feedback literacy mediate the relationship between GenAI use and learning outcomes: students who actively orchestrate prompts, evaluate AI suggestions, and integrate them with human feedback derive greater benefit than those who copy output uncritically (Lee, 2024; Shi et al., 2025). AI literacy courses that foreground these skills appear to cultivate more critical, reflective tool use (Anders, 2025).

2.3 Cognitive Load and Scaffolding

From a cognitive load perspective, GenAI can reduce extraneous load by clarifying instructions, offering worked examples, or rephrasing confusing passages, thereby freeing resources for higher-order reasoning (Meyer et al., 2024). At the same time, over-scaffolding may suppress germane load if students bypass productive struggle. Studies of human–AI collaborative writing highlight the need to distinguish between assistance that supports schema construction and shortcuts that obscure key problem-solving steps (Fan et al., 2025; Gkintoni et al., 2025).

2.4 Integrity and Equity

Policy analyses stress that AI-writing detectors provide probabilistic signals and should not be treated as conclusive evidence of misconduct (Turnitin, 2023; Jisc, 2025). Instead, institutions are encouraged to redesign assessments to keep learning visible through process evidence, oral defenses, and authentic tasks (UNESCO, 2023). Equity-focused work warns that GenAI could amplify existing disparities if only some students receive guidance on ethical, effective use or have reliable access to tools (OECD, 2024). Conversely, well-designed AI-augmented feedback can support multilingual writers and students with disabilities by providing more frequent, individualized formative input (Fan et al., 2025; OECD, 2025).

Chapter 3: Methodology

3.1 Design

The study adopts an explanatory sequential mixed-methods design. In phase one, quasi-experimental comparisons are conducted between online graduate course sections implementing AI-augmented feedback cycles and sections using existing feedback practices. Phase two employs interviews and focus groups with students and instructors to interpret quantitative findings and surface contextual nuances.

3.2 Participants and Setting

Participants will be graduate students enrolled in fully online education and public administration programs at a large public university. Courses are writing-intensive and include major assignments such as policy briefs and research papers. Approximately 200 students across eight course sections are expected to participate in the survey phase; 24–30 students and 10–12 instructors will take part in interviews.

3.3 Intervention: AI-Augmented Feedback Cycle

In treatment sections, instructors will introduce a structured feedback cycle comprising: (a) transparent policy framing GenAI as a permitted feedback partner; (b) guided prompt templates for requesting critique on argument structure, evidence use, and clarity; (c) a requirement for students to submit a brief “feedback-to-revision memo” describing how AI and human feedback informed changes; and (d) opportunities to discuss challenges and ethical questions. Control sections will continue existing practices, which emphasize human instructor feedback and optional peer review without explicit AI guidance.

3.4 Data Collection and Analysis

Quantitative data will include pre- and post-course surveys measuring writing self-efficacy, perceived workload, and integrity attitudes, as well as assignment grades scored with a validated rubric. Hierarchical linear models will estimate treatment effects while accounting for course- and instructor-level clustering. Mediation analyses will examine whether changes in feedback-use behaviors explain any writing gains. Moderation analyses will test differences by first-generation status, language background, and disability accommodations.

Qualitative interviews and focus groups will explore how students experience AI-augmented feedback, how they interpret integrity rules, and whether the intervention affects their sense of belonging and fairness. Thematic analysis will be used to identify cross-cutting patterns and divergence across subgroups (Braun & Clarke, 2006).

(The latter part of the thesis has been intentionally omitted to protect data privacy)

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