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Teaching and learning at the intersection of artificial intelligence, academic integrity, and assessment innovation: A rapid scoping review protocol

Michael Holden*[1], Naomi Paisley[2], Myke Healy[2], Sarah Elaine Eaton[2], Nadia Delanoy[2], & Amy Burns[2]

Abstract
For three years, teachers and teacher educators have been struggling to respond to the advent of generative artificial intelligence (GenAI) and its implications for teaching and learning. Building on DeLuca et al.'s (2025) AI^3 framework, this paper is situated at the intersections of artificial intelligence, academic integrity, and assessment innovation: three critical 'AIs' for the current moment. Owing to a dearth of literature reviews at this intersection, this paper presents a rapid scoping review protocol for AI^3 in preservice teacher education. The protocol follows the Joanna Briggs Institute's updated manual for scoping reviews and the Preferred Reporting Items for Systematic Reviews Meta-Analysis (PRISMA) reporting standards (Aromataris & Munn, 2020). The studies included in the review will be analyzed for insights on these topics, particularly the innovative practices possible in an age of GenAI. Our findings will be relevant to teacher educators in particular and more broadly to educational researchers and practitioners interested in integrity, innovation, and defensible practice in ever-shifting GenAI spaces.

Keywords
Canada, classroom assessment, generative artificial intelligence, K-12 education, teacher education

[1]University of Winnipeg, [2]University of Calgary
***Corresponding author**: mi.holden@uwinnipeg.ca

Introduction

Interest in artificial intelligence (AI) has exploded in the past three years. From general media (Klein, 2025) to public policy (Fengchun & Holmes, 2023; Office of Educational Technology, 2023) to educational research (Bearman et al., 2024; Lodge et al., 2023), mounting attention is now being paid to questions of what it means to teach, learn, and assess in a so-called 'age of AI' (Cao, 2022; Daugherty & Wilson, 2024). Most of this discourse focuses on generative artificial intelligence (GenAI)[1], an AI subfield describing models trained on terabytes of data to generate novel content in response to user prompts (Dehouche, 2021; Rudolph et al., 2023). GenAI extends far beyond OpenAI's ChatGPT–now eponymous like Hoover, Kleenex, and Xerox of yesteryear. An ever-expanding roster of GenAI products has appeared, including tools for generating language, code, images, video, and music (Fengchun & Holmes, 2023). The result is ubiquity. GenAI tools have been embedded in platforms like Google's billion-user search engine (Stein, 2025) and Microsoft's Windows and Office suite (*AI-powered features in Windows 11*, n.d.), and a growing number of nations have appointed ministers with an explicit AI focus (e.g., Prime Minister of Canada, 2025; *Clara Chappaz*, n.d.; United Arab Emirates, 2022). Little wonder, then, that there are now repeated calls to attend to the transformative promise and peril of this quickly changing landscape (Cope et al., 2021; Corbin et al., 2025).

In education, responses to GenAI have been as wide-ranging as the tools themselves. Institutions have banned GenAI tools outright (e.g., *Sciences Po bans the use of ChatGPT without transparent referencing*, 2023), implemented then rescinded both bans and custom tools (e.g., Banks, 2023; Carvalho, 2023; Seshadri, 2024), explicitly embraced GenAI (e.g., Chinook's Edge School Division, 2024; Matsuzoe, 2023; Ministry of Education, South Korea, 2023), and left decisions about GenAI use up to individual instructors' discretion (e.g., University, 2024; Centre for Teaching and Learning, n.d.). These decisions have been undergirded by various conceptual frameworks, including Perkins et al.'s (2024) Artificial Intelligence Assessment Scale (AIAS), the University of Sydney's two-lane approach (Bridgeman et al., 2024), Hamilton et al.'s (2023) four scenarios, and the Montréal Declaration (*Montréal declaration for a responsible development of artificial intelligence*, 2018), among others. Educators and researchers have written of GenAI's transformative potential

[1]For a primer on GenAI and the lineage of AI research more generally, see Banh and Strobel (2023), Cope et al. (2021), and Kalota (2024).

(Rudolph et al., 2023), its society-changing implications (Sætra & Fosch-Villaronga, 2021), and a need to "minimize the damage" to education and humanity at large (Hamilton et al., 2023, p. 1). The field is, in short, a house divided.

The seemingly swift arrival of GenAI and the ongoing inconsistency of educational reactions necessitate research into what teaching, learning, and assessment practices will best serve students, instructors, and society moving forward (Fengchun & Holmes, 2023; Office of Educational Technology, 2023; Volante et al., 2023). In our context–preservice teacher education at a research-intensive university–there is a particular need to examine (1) how teacher educators can best design teaching, learning, and assessment opportunities and (2) how preservice teachers develop the professional capacity to design learning opportunities amidst GenAI. This need is also rapidly shifting. Each month, it seems, new tools gain traction (e.g., DeepSeek-AI., 2025); new data arise about GenAI use (Gruzd et al., 2025); and new misconceptions take root as teachers and teacher educators continue to work without a robust understanding of the implications of GenAI for their practice (Kotsis, 2025). Put simply, teachers and teacher educators need to know what innovative practices are possible with GenAI in education.

The purpose of this paper is to describe a rapid scoping review protocol to methodologically anchor our work (Tricco et al., 2015). The rapid scoping review will examine current research at the intersections of artificial intelligence, academic integrity, and assessment innovation in preservice teacher education–what we call AI^3 (DeLuca et al., 2025). Specifically, this paper describes the protocols we will use to synthesize evidence through a forthcoming rapid scoping review (Peters et al., 2022). Standard practice for systematic, scoping, and rapid reviews begins with "a preliminary investigation of the literature. . . to determine if studies are available on the topic of interest, and especially to confirm if other comparable literature reviews already exist" (Aromataris & Munn, 2020, p.16). We did not find any such reviews, and consequently, we are confident this rapid review will contribute valuable, timely, and relevant information at AI^3's intersections. We chose a rapid scoping review because previous successful efforts have shown that such reviews effectively inform various stakeholders about rapidly emerging research areas (Wollscheid & Tripney, 2021), such as the one explored in this study. While GenAI is not a new challenge–educators have faced it for three years, and artificial intelligence in education (AIED) research far predates lay user interest in GenAI (Dehouche, 2021)–the GenAI landscape is demonstrably different today than it was six months ago, and we suspect the landscape will yet change more. We contend that a rapid scoping review is therefore appropriate for documenting the current scope of research at the AI^3 intersection. To support transparency and systematize our search (Peters et al., 2022), this article's chief purpose is to articulate our *a priori* protocol, consistent with extant rapid scoping review methods (Aromataris & Munn, 2020; Munn et al., 2022). Before describing these methods, we detail the AI^3 intersection, which forms the context of our search.

Background

This rapid scoping review focuses on the intersections of three distinct fields that have crashed together in the current landscape: artificial intelligence, academic integrity, and assessment innovation. DeLuca and colleagues (2025) present these intersections as AI^3, arguing that explicit attention to each 'AI' is critical for teaching, learning, and assessment moving forward. We frame GenAI as AI here for three reasons: (1) lexical convenience, (2) the tendency for lay users (including educational researchers) to refer to GenAI and AI interchangeably, and most importantly, (3) because cultural and educational concerns about the role of artificial intelligence and technology far precede the explosive attention GenAI has garnered since 2022. In short, while we agree with clarifying comments that GenAI and AI have critical distinctions, our fundamental argument centres on the importance of attending to the promise and peril of all AI applications, not just those GenAI tools teachers and students can access with ease today. The pedagogical concerns of 2025 are focused on GenAI but are also transferable to other AI applications, including those most educators have not (yet) heard of. We further echo Peters et al.'s (2022) contention that reviews should attend to and include the language readers use (e.g., [un]intentionally interchanging GenAI and AI) to increase recognizability and therefore use. In the sections that follow, we provide a brief orientation to research from each area.

Artificial Intelligence

Artificial intelligence research has existed in various forms since the 1950s (McCarthy et al., 2006; Turing, 1950). Broadly defined, artificial intelligence refers to "the branch of computer science that deals with the simulation of intelligent behaviour in computers" (Akgun & Greenhow, 2022, p. 431). GenAI is the most relevant subfield to the current moment, focusing on tools that use statistical analyses, algorithms, and similar protocols to generate new text in response to user prompts (Fengchun & Holmes, 2023). Such 'text' may include the written word, as well as images, video, music, and other creations whose generation have historically been seen as distinctly 'human' pursuits (Fornäs, 1997; Lyu et al., 2022). Beyond the obvious attention to GenAI since 2022, AIED research examines how teachers and other constituents use, learn from, or learn with these tools to enhance their teaching and learning efforts in diverse contexts (Cope et al., 2021). Molenaar (2022), for example, argued that "the central role of AI in education ... is to facilitate learning and teaching processes" (p. 633), not to have artificial intelligence tools supplant the intellectual work done every day by students, teachers, teacher educators, or society at large. To AIED researchers, then, humans and GenAI tools might be seen as co-creators (Lyu et al., 2022; Turchi et al., 2023), with the roles that humans and GenAI tools undertake depending on learners' practical and pedagogical goals (Lodge et al., 2023).

Despite these aspirations, much of the attention paid to GenAI is rooted in concern. Researchers and lay users compare GenAI tools to "bullshit spewers" (Rudolph et al., 2023, p. 342) and have long raised concerns about the so-called ouroboros effect (Campbell, 2024), where GenAI outputs, once unleashed, are trained on both human-generated and machine-generated content (Hua & Raley, 2020). More recently, a preprint by (Kosmyna et al., 2025) sparked widespread public conversation about cognitive debt and the risk of relying on GenAI outputs at the expense of human cognition and creativity. Such tools have also been criticized for their effects on the environment (Berthelot et al., 2025), human labour (Steinhoff, 2021), intellectual property rights (*Disney Enterprises Inc. v. Midjourney Inc.*, 2025), and longstanding cultural biases (Liang et al., 2023). The promise and peril of GenAI tools have complexified already difficult fields, not least of all the work of teachers and learners. For these reasons, DeLuca and colleagues (2025) contend that explicit attention to GenAI is needed but in-and-of-itself insufficient, requiring the parallel anchors of academic integrity and assessment innovation.

Academic Integrity

Academic integrity carries no singular definition (Eaton, 2024) but has been characterized as a commitment to six fundamental values: honesty, trust, fairness, respect, responsibility, and courage (International Center for Academic Integrity, 2021). Given their interconnections, these values are sometimes treated synonymously (Macfarlane et al., 2014), as in familiar logic loops such as, 'It takes courage to be honest, and not being honest is disrespectful and undermines trust.' Yet each term has its own theoretical, etymological, and cultural roots. Consider honesty and fairness. As Fleeson et al. (2022) describe, honesty can refer either to specific acts–an individual choosing to tell the truth, 'be true to themselves,' or simply refrain from lying–or to a latent trait, as in 'Taha is an honest person.' Individuals vary in their standards of honesty (Cherrington & Cherrington, 1993), and their espoused commitment to honesty may change in specific circumstances (Wells & Molina, 2017). Fairness, likewise, is not consistently defined (Rasooli et al., 2019). Some teachers define fairness as enacting equality–treating all students equally and consistently to mitigate bias–while others root fairness in equity and argue for the need to account for and redress systemic injustices (Coombs et al., 2018). Looking broadly at academic integrity and its history in higher education, Christensen Hughes (2022) criticizes what she describes as centuries of institutional ethical failures and calls on academic leaders to "ensure that these values [of academic integrity] are explicitly embedded in university curricula, as well as in the selection criteria for administrators, faculty, and staff" (p. 53). Put differently, academic integrity scholars argue that these values are fundamental to the educational process and should therefore take centre stage in discussions of teaching and learning (Bertram Gallant & Rettinger, 2022).

Synthesizing the extant scholarship, Eaton (2024) proposed an eight-fold comprehensive framework to ensure academic integrity discussions extended beyond admonitions like 'don't cheat.' The eight elements include (1) everyday ethics, such as civility and compassion; (2) institution ethics, including whether ethics policies exist and how those policies are articulated or enforced; (3) ethical leadership, demonstrated by how system leaders model integrous behaviours; (4) professional and collegial ethics, as articulated in regulatory documents like Alberta Education's (2023) teaching quality standard; (5) instructional ethics, enacted through the decisions teachers take in the course of their duties; (6) student academic conduct, the most well-known branch of academic integrity, referring to how students conduct themselves in educational spaces; (7) research integrity ethics, including ethical design and review processes; and (8) publication ethics, which govern how knowledge is created and disseminated in academia. Academic integrity therefore takes a comprehensive view: one that extends beyond traditional notions of academic responsibility to describe how the principles of honesty, trust, fairness, respect, responsibility, and courage permeate all aspects of education.

In the context of GenAI, it is worth re-emphasizing that academic integrity requires attention to more than just plagiarism, cheating, or student misconduct. For example, the Montréal Declaration for the responsible development of artificial intelligence is explicitly

> addressed to any person, organization, and company that wishes to take part in the responsible development of artificial intelligence, whether it's to contribute scientifically or technologically, to develop social projects, to elaborate rules (regulations, codes) that apply to it, to be able to contest bad or unwise approaches, or to be able to alert public opinion when necessary. (*Montréal declaration for a responsible development of artificial intelligence*, 2018, p. 6)

As in broader academic integrity research, GenAI-academic integrity is a *shared* duty held by students, instructors, institutions, and society writ large. Academic integrity advocates have therefore called for explicit opportunities for students and instructors to learn about the (un)ethical (mis)uses of GenAI and how those standards apply in specific contexts (Dieterle et al., 2024; Gros et al., 2022). Such considerations inevitably inform how teachers and students assess, in large part because (mis)conduct concerns typically centre on assessment and evaluation. Ethical assessment amidst GenAI therefore leads to a third intersection: assessment innovation.

Assessment Innovation

Assessment innovation research examines new-in-context approaches teachers and students use "to improve teachers' classroom assessment practice and support the fundamental goal of advancing student learning" (DeLuca et al., 2024, p. 109). For added clarity, assessment refers to the iterative process of gathering information and using multiple forms of evidence to make decisions about students' performance and progress (Black & Wiliam, 2018; Friesen, 2009). Just as AI encompasses more than just GenAI, and just as academic integrity requires more than simply saying 'don't cheat,' assessment extends far beyond the assignments teachers create or how they communicate their judgments through feedback and grades (Cowie & Harrison, 2016; Graham et al., 2018). We especially emphasize that assessment is a process. That process attends to the endless inferences that teachers, students, and other educational actors make about student learning with an eye to how those inferences will be used to benefit students, teachers, and society (McMillan, 2013; Shepard, 2019). Because they cannot guarantee that what was *taught* will be *learned* (Davis & Sumara, 2006)–at a given time, in a given way, to a given depth–teachers must assess and work with students to navigate challenges and contextual dilemmas (Frannsson & Grannäs, 2013).

DeLuca et al. (2024) therefore present assessment innovation as a necessary way for teachers to attend to their practice over time. They identify multiple longstanding assessment challenges, including an overemphasis on grades instead of learning, data overload, conflicting orientations toward assessment, and inequitable assessment practice (see also DeLuca et al., 2019; Fullan & Hargreaves, 2013). Such assessment challenges have only been exacerbated by GenAI. While the flavour of these challenges is unique to the present moment–instructors in 2012 would have little reason to suspect a machine wrote a student's essay whole-cloth–the underlying dilemmas of validity, reliability, and defensible assessment practices are strikingly similar (DeLuca et al., 2024).

We emphasize assessment innovation within the AI^3 framework for two reasons (DeLuca et al., 2025). First, as we have already noted, GenAI tools and public discourses continue to proliferate, leading to repeated calls to transform assessment practices that no longer meet teachers' and students' needs (Corbin et al., 2025; Volante et al., 2023). Teachers and other constituents have already been forced to reckon with the sociocultural effects GenAI is having on learning and behaviour (Kosmyna et al., 2025; Shepard, 2019). If teachers are to assess sustainably, defensibly, and authentically (Boud, 2000; Cope et al., 2021), they must at a minimum consider what teaching and learning activities most align with their pedagogical goals (Fengchun & Holmes, 2023). Put another way, they must enter the assessment innovation cycle: identify a challenge in their practice, weigh the dilemmas that challenge invokes, respond to that challenge with some small-i, local innovation, and assess whether that innovation helps propel their work (DeLuca et al., 2024).

Our second reason for foregrounding assessment *innovation* rather than assessment *challenges* or "just good teaching" (Ladson-Billings, 1995, p. 159) is rooted in innovation's discursive implications. Assessment in education often relies on top-down responses that assume universal challenges have universal solutions that can be resolved if teachers implement them 'with fidelity' (DeLuca et al., 2024; Timperley, 2015), ignoring the complexities of teaching, learning, and assessment as they arise in specific contexts and local conditions (Black & Wiliam, 2018; Rees Lewis et al., 2019; Smith & Smith, 2020). Focusing on teachers' assessment innovations supports the view that a "shared responsibility for student learning . . . is important for the design, assessment, and improvement of academic programs" (Hutchings et al., 2011, p. x). While we acknowledge teachers' shared assessment challenges, we echo the broad base of assessment research highlighting the importance of instructors developing their capacity to design assessment opportunities that fit local teaching and learning needs (DeLuca et al., 2023; Pastore & Andrade, 2019). We also support Bearman et al.'s (2016) contention that "improving assessment practices requires reconciling issues from different levels of consideration: conceptual, interpersonal and pragmatic" (p. 17). Improving assessment–including in response to GenAI's promise and peril–fundamentally requires engagement with teachers' conceptual understandings, how they and their students interact with GenAI, and the pragmatic realities of teaching and learning that are fundamentally local. When Corbin et al. (2025) call for structural assessment changes, they invoke not just the top-down policies of institutions. They necessarily call on teachers to ask "how we can design assessments that maintain their validity in an AI-enabled world" (Corbin et al., 2025, pp. 8-9). At its core, this is a question of assessment innovation. Innovation in this context does not necessarily require never-before-seen changes to assessment practice. Classroom assessment researchers have long called for renewed focus on validity via a focus on "rich, challenging, and authentic learning goals . . . [that lead to] internalized understandings and improved performance" (McMillan, 2013, p. xxi). Assessment innovation in the age of GenAI is not necessarily a matter of total transformation (though in some contexts, this may happen). Instead, assessment innovation recognizes the necessary role of centring teachers and students in ongoing, iterative conversations about the challenges they are facing, and how they can leverage the best evidence available to make meaningful changes in the work they do together (DeLuca et al., 2024).

AI^3 attempts to orient attention toward three essential features of contemporary education: the ubiquity of GenAI tools and their implications for learning and society (AI one); the role of educational ethics as presented in comprehensive academic integrity (AI two); and the process of local, teacher-led iterations to improving classroom assessment as represented by assessment innovation (AI three). This framing sets the stage for our rapid scoping review protocol, which we describe in the following sections.

Objective

This protocol specifies how this rapid scoping review will examine how teacher educators and preservice teachers within K-12 education navigate AI^3. As we have described, the purpose of this research is to provide guidance on how to ethically teach and assess in an era of GenAI. We situate the review in AI^3 because all three perspectives are necessary in the current moment. As has been argued elsewhere,

> Ignoring artificial intelligence is a head-in-the-sand approach where students are left to use (or not use) AI tools without pedagogical support, such as when a school articulates no AI policy whatsoever ... Similarly, ignoring academic integrity–"the values, behaviours, and conduct" of people in academic spaces (Macfarlane et al., 2012, p. 339)–has serious implications for privacy, data literacy, and equity ... Finally, ignoring assessment principles–and particularly the assessment innovations teachers leverage in their daily practice (DeLuca et al., 2024)–risks creating inconsistencies between espoused pedagogies and students' actual assessment experiences (Black & Wiliam, 2018). (DeLuca et al., 2025, p. 2)

As a team of educational researchers, teachers, and teacher educators, we are particularly interested in the implications of AI^3 for teacher practice, especially teacher education. Teacher education–including both undergraduate teacher education and the continuum of teacher learning that occurs across pre- and in-service teacher education–has long been recognized as critical to teachers' ability to face the myriad demands of public education (Beck & Kosnik, 2017; Darling-Hammond, 2000). We therefore anchor our research in the following question: How can integrating artificial intelligence, academic integrity, and assessment innovation enhance pedagogy in teacher education? The goal is to contribute to improved teaching practices for preservice K-12 teachers and teacher educators, and effectively support teachers to lead classrooms in a world increasingly influenced by GenAI.

Methods

This protocol follows Joanna Briggs Institute's (JBI) updated reviewer manual for scoping reviews (Aromataris & Munn, 2020). The reports will follow the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) (Page et al., 2021).

Eligibility Criteria

Eligibility criteria articulate which studies will be retained throughout the review. Here, we use Peters et al.'s (2022) population, concept, and context (PCC) framework, which articulates a search's foci for (a) "participants of interest" and their relationship to the review topic (p. 961); (b) "the key issue or topic that the scoping review will explore" (p. 961), including any key definitions, theoretical frames, or methodologies; and (c) "the location and/or field of the concept and/or participants" (p. 962), including any relevant settings, locations, or points in time. Included studies will (1) examine artificial intelligence, academic integrity, and assessment innovation, (2) be focused on preservice K-12 teachers enrolled at a research-intensive university, and (3) be published in English between 2022 and 2025. Studies focusing on in-service teachers or general K-12 populations, without a preservice teacher population, will be excluded. Table 1 elaborates on these criteria, which were established before screening. Iterative piloting will refine operational definitions for borderline cases, but initial decisions will be grounded in these *a priori* parameters.

Table 1. Inclusion and Exclusion Criteria for Study Selection

	Inclusion criteria
1	Studies must examine the intersection of artificial intelligence, academic integrity, and assessment innovation.
2	The population must be preservice teachers who are training for K-12 education roles and are enrolled at a research-intensive university.
3	Peer-reviewed empirical research, theoretical papers, and systematic reviews published from 2022 to 2025 in English.
	Exclusion criteria
1	Studies focusing on in-service teachers, higher education students not in teacher preparation programs, or K-12 students.
2	Articles addressing only one or two of the central themes (artificial intelligence, academic integrity, assessment innovation) rather than their intersection.
3	Editorials, opinion pieces, conference abstracts only, or non-English texts.

Given the nature of a rapid scoping review, we follow Munn et al. (2022) and Peters et al. (2022) by adopting broad inclusion criteria to provide comprehensive insights for readers and reviewers. Texts that do not meet the eligibility criteria will be excluded from the review.

Population

This rapid scoping review is focused on two related populations: (1) teacher educators in university-based teacher education programs and (2) the preservice teachers enrolled in such programs. Included studies will focus explicitly on teacher education for preservice teachers, that is, programs whose graduates typically go on to be certified as kindergarten to grade 12 (K-12) teachers. Studies will not be excluded based on more granular participant foci such as gender, age, or race. While we support the ongoing work to conceptualize pre- and in-service teacher education as a continuum of ongoing professional learning (Beck & Kosnik, 2017; Timperley, 2015), for feasibility, this rapid scoping review will exclude studies focused on in-service teacher education or other populations beyond teacher educators and preservice teachers. Examining how in-service teachers navigate AI^3 is an important question but is beyond the scope of the present review.

Concept

The central concept of this review is the integration of artificial intelligence tools into assessment practices in ways that affect or relate to academic integrity within preservice K-12 teacher preparation. The review includes studies presenting empirical data, systematic reviews, or theoretical analyses that address all three themes as they intersect in the context of university-based preservice teacher education. As suggested by the AI^3 framework (DeLuca et al., 2025), the core concepts of this review are the concurrent intersections of academic integrity, artificial intelligence, and assessment innovation. Taken together, the AI^3 intersections present a complex and evolving landscape that challenges traditional notions of education and evaluation. Studies will be included if they address the AI^3 intersection by explicitly engaging the concepts of academic integrity, GenAI, and classroom assessment or associated terms. These terms are detailed in our search strategy (Table 2), which we describe later in this protocol. Studies will be excluded if they do not engage the AI^3 intersections. For example, while DeLuca et al. (2024) engage assessment innovation, that article does not engage academic integrity or GenAI and so would be excluded from the review.

Context

The context for this review is limited to formal teacher education settings. Consistent with the population criteria, studies will be included if their context examines AI^3 intersections in teacher education programs, which are typically (though not always) located in universities or schools of education. Broadly, then, the context for this review is higher education; other institutional contexts will not be included.

Study Design

This scoping review will include qualitative, quantitative, mixed methods, theoretical, and opinion studies. This broad approach aligns with the nature of scoping reviews, which allows for the inclusion of varied source types. The review will not be limited by geographic location. Due to feasibility considerations, only English-language sources will be included (Peters et al., 2022) as all authors are proficient in English. Sources reviewed will include academic articles, conference presentations, papers, and grey literature, with the inclusion of grey literature aiming to capture recent, unpublished research in the field. Sources such as social media postings, product information, and advertising will be excluded. Because of the rapidly shifting landscape of GenAI tools and the notable change in public awareness since ChatGPT 3.5's release in November 2022 (Dehouche, 2021; Rudolph et al., 2023), we will focus on articles published since this date.

Information Sources

We will consider a limited number of transparent and reproducible library or bibliographic databases. To conduct a comprehensive search, we will focus on five interdisciplinary databases: Academic Search Complete (EBSCO), Education Research Complete, ERIC (EBSCO), Web of Science, and Scopus. Further, we will conduct targeted searching for grey literature, including searching Google Scholar for conference presentations and reviewing relevant conference websites.

Search Strategy

To develop a robust and transferable search strategy, we first designed and tested our search terms in ERIC, an educational research database hosted on the EBSCO platform. Once this initial search approach was refined and optimized, we adapted the same set of search strategies for use in the other databases included in our review. This stepwise approach allowed us to ensure the search strategy was comprehensive and effective in one database before extending it to others in the forthcoming rapid scoping review.

Study Selection

The study selection process will be conducted in two stages. To ensure studies are strictly scoped to these concepts, we will implement a predefined eligibility scheme anchored by operational definitions and concrete inclusion and exclusion criteria. Before screening, the three target concepts will be explicitly defined based on existing literature (Page et al., 2021; Moher et al., 2010; Tricco et al., 2015), and their operational boundaries will be documented in a codebook shared with all reviewers. This codebook will include clear definitions for each concept, specific examples of what constitutes inclusion and exclusion for each concept, and guidance on handling borderline cases.

Both the title and abstract and full text screening forms in Covidence will be tailored to include checklist items or questions mapped exactly to the three concepts. For a study to move forward, it must receive a ”Yes” on all three concept-relevant criteria from both reviewers. During the pilot phase, reviewers will independently assess 50 records and subsequently meet to discuss any discrepancies. This phase is designed not only to standardize the application of criteria but to refine operational guidance for tricky cases, based on reviewers' experiences with real records.

When the first and second reviewers disagree regarding a study's relevance to one of the three concepts, the third reviewer will be provided with the codebook, the screened record, and reviewers' justifications. The third reviewer will adjudicate based on the operational guidance, and if consensus cannot be reached, the full team will discuss and document the decision. Every stage including reasons for exclusion at both title and abstract and full text phases will be systematically recorded within Covidence and reported in the PRISMA flow diagram.

Data Extraction

Our data extraction process will involve a team of three reviewers (R1, R2, and R3). We will conduct a calibration exercise using five randomly selected studies to ensure consistency

Table 2. Proposed Data Extraction Table

#	Query	Limiters/Expanders	Results
S1	DE "integrity" or "ethics"	Search modes - Find all my search terms	27,348
S2	DE "assessment design" or "classroom assessment"	Search modes - Find all my search terms	1,613
S3	DE "Artificial intelligence" or "GenAI"	Search modes - Find all my search terms	4,977
S4	DE "preservice teacher" or "teacher trainee" or "student teacher" or "teacher candidate"	Search modes - Find all my search terms	26,508
S5	DE "K-12 Education" OR DE "Elementary Education" or DE "Secondary Education" AND (academic integrity) AND (artificial intelligence or ai or a.i.) AND (assessment or assignment)	Search modes - Find all my search terms	5
S6	TI (academic N2 (integrity or plagiarism or conduct or misconduct or mis-conduct or honesty or dishonesty or dis-honesty)) OR AB (academic N2 (integrity or plagiarism or conduct or misconduct or mis-conduct or honesty or dishonesty or dis-honesty)) OR KW (academic N2 (integrity or plagiarism or conduct or misconduct or mis-conduct or honesty or dishonesty or dis-honesty))	Search modes - Find all my search terms	1,920
S7	DE "Intelligent Tutoring Systems" OR DE "Artificial Intelligence" OR DE "Natural Language Processing"	Search modes - Find all my search terms	7,247
S8	DE "Assessment Innovation" OR DE "Classroom assessment" OR DE "Assessment Design"	Search modes - Find all my search terms	10,769
S9	TI ((artificial or computational or machine) N2 intelligence) OR AB ((artificial or computational or machine) N2 intelligence) OR KW ((artificial or computational or machine) N2 intelligence)	Search modes - Find all my search terms	2,859
S10	TI (professor* or instructor* or teacher*) OR AB (professor* or instructor* or teacher*) AND (academic integrity) AND (artificial intelligence or ai or a.i.) AND (assessment or assignment)	Search modes - Find all my search terms	20
S11	TI ((cheating or plagiarism or eplagiarism or e-plagiarism or echeat* or e-cheat*)) OR AB ((cheating or plagiarism or eplagiarism or e-plagiarism or echeat* or e-cheat*)) OR KW ((cheating or plagiarism or eplagiarism or e-plagiarism or echeat* or e-cheat*))	Search modes - Find all my search terms	2,928
S12	TI ((exam* or test* or assignment* or assessment* or remote or online) N3 proctor*) OR AB ((exam* or test* or remote or online) N3 proctor*) OR KW ((exam* or test*) N3 proctor* or remote or online)	Search modes - Find all my search terms	867
S13	S1 or S6 or S11	Search modes - Find all my search terms	29,666
S14	S2 or S8 or S12	Search modes - Find all my search terms	2,480
S15	S3 or S7 or S9	Search modes - Find all my search terms	7,769
S16	S4 and DE (K-12 education or elementary education or elementary school or primary school or primary education) and S11 or S7 or S8	Search modes - Find all my search terms	7,538
S18	S1 and S6 and S11 or S2 and S8 and S12 or S16	Search modes - Find all my search terms	21
S19	OR DE "Undergraduate Study" OR DE "Undergraduate Student" OR DE "Universit*" OR DE "College Student" AND (academic integrity) AND (artificial intelligence or ai or a.i.) AND (assessment or assignment)	Search modes - Find all my search terms	9
S20	S13 or S14 or S15 or S16	Limiters - Date Published: 202211101-20241231; Search modes - Find all my search terms	70,919

Note: TI = Title, (article/document title); DE = Descriptor (equivalent to Subject or Subject Heading); KW = Keyword; AB = Abstract; N = Near, meaning the searcher wants to find one term near another.

and clarity of the extraction as indicated in Table 3 for the application. The reviewers will collaboratively assess whether the data extraction template effectively captures the essential elements of each study (Tricco et al., 2015). This collaborative phase will continue until the team reaches a consensus as standardization is crucial for reliable data extraction (Peters et al., 2022). The full data extraction will commence after this phase, using the finalized table. R1 and R2 will systematically organize the information from each study (Tricco et al., 2015). Where discrepancies or uncertainties arise, R3 will mediate and resolve disagreements (Lunny et al., 2021). This structured data extraction approach is intended to enhance the findings' reliability and consistency by minimizing bias through a comprehensive extraction process.

Risk of Bias Assessment and Critical Appraisal

Bias will be mitigated through several strategies consistent with Stone et al. (2023). As described above, study selection

Table 3. Search Results from Rapid Scoping Review Search in the ERIC database

Component	Description
Citation	Source's citation data according to APA 7 guidelines
Authors	The name(s) of the author(s), including last name and first initial
Country	The country of the institution where the author(s) is/are affiliated, chosen from a drop-down list
Year of Publication	The year the source was published
Type of Document	The type of source, chosen from a drop-down list: 1) blog, 2) book, 3) book section, 4) conference paper, 5) conference proceedings, 6) journal article, 7) magazine article, 8) newspaper article, 9) thesis, or 10) webpage
Participants	The source's participants, chosen from a drop-down list: 1) K-12 faculty, 2) college/university faculty, 3) students, 4) teaching assistants, 5) academic administration, 6) assessment developers, or 7) multiple
Purpose(s)	The purpose of the source as indicated by the authors; includes direct quote(s) and page numbers
Research Question	The research question(s) as indicated by the authors
Data Collection	The source's information on how the data was collected
Result(s)	The study results, as outlined by the author(s)
Limitation(s)	The source's limitations, as outlined by the author(s)
Conclusion(s)	The source's conclusions, as outlined by the author(s)
Academic Integrity focus	Academic integrity focus, chosen from a drop-down list: 1) comprehensive, 2) K-12, or 3) higher education
AI Tool(s) used	The source's type of artificial intelligence tool(s) under study
Assessment type	The source's type of assessment under study; for example, "formative assessment," "in-class activities," "essay," or "research project"
Discipline	The source's associated discipline, chosen from a drop-down list: 1) Social Sciences, 2) Humanities, 3) Computer Science/Engineering, 4) Natural Sciences, 5) Fine Arts, or 6) Other

Note: Adapted from Lunny et al. (2021) and Tricco et al. (2015).

will be guided by the *a priori* eligibility criteria, and each screener (R1 and R2, with R3 in cases of disagreement) will independently implement the screening procedures. We will mitigate potential publication bias (for example, excessive praise or skepticism toward GenAI) by drawing on studies from interdisciplinary resources. To strengthen the validity of our findings (Wollscheid & Tripney, 2021), we will critically appraise each study's methodology using Critical Appraisal Skills Programme (2022) tools. These instruments will enable R1 and R2 to independently and systematically evaluate the quality of evidence in each study. By incorporating these measures, we aim to maintain a high methodological rigour standard despite our scoping review's rapid nature. This approach allows us to balance the need for timely results with the imperative of producing trustworthy and robust findings.

Data Analysis

In rapid scoping reviews, thematic analysis serves as a foundational approach for synthesizing qualitative data across a diverse set of sources. This analytical strategy is particularly useful when the literature reviewed includes heterogeneous study designs, varied methodological quality, and broad contextual differences, all of which are common in educational research focused on emerging topics such as artificial intelligence, academic integrity, and assessment innovation. The process begins with familiarization as reviewers immerse themselves in the extracted dataset, developing an in-depth understanding of the material. They then proceed to code the data, systematically identifying features of interest that may recur across studies. These initial codes are subsequently grouped into potential themes, with the research team searching for underlying patterns that provide insight into the overarching research questions guiding the review.

To achieve consistency and transparency in analysis, the team will draw on the influential six-phase method articulated by Braun and Clarke (2006). This framework involves moving from data familiarization to code generation, then to theme development, followed by iterative reviewing, defining, and naming of themes. In the context of a rapid scoping review, this structured thematic analysis supports an efficient yet rigorous synthesis, allowing the research team to identify both explicit and latent patterns in the literature while documenting any limitations or potential sources of bias in the evidence base. This approach will allow for a comprehensive understanding of the overarching themes present in the reviewed materials (Lunny et al., 2021; Wollscheid & Tripney, 2021). In the interest of transparency and scientific rigour, the researchers will methodically document and communicate any potential limitations or biases inherent in the included studies. This critical self-assessment will provide readers with a clear understanding of the scope and constraints of the research findings (Peters et al., 2022; Wollscheid & Tripney, 2021).

Future Directions

This rapid scoping review will explore how future educators can effectively navigate AI^3: the intersections of artificial intelligence, academic integrity, and assessment innovation, with a particular focus on teacher education as a key context in higher education. The study aims to provide valuable insights that will directly contribute to improved teaching and learning. In particular, the review will address a critical research gap in preservice teacher and teacher educator perceptions of GenAI in classroom contexts (e.g., Kotsis, 2025). We will use our analysis to formulate a set of recommendations for subsequent research in AI^3. These recommendations will address identified gaps in current knowledge and propose avenues for further exploration (Peters et al., 2022). Rapidly yet robustly identifying the current state of knowledge at the AI^3 intersection will directly contribute to ongoing efforts to support preservice teachers and teacher educators in reflecting on their approaches to teaching, learning, and assessment in ways that reflect the ethical and technological complexities of this GenAI age. We see this work as critical both to our own local context–a preservice teacher education program in western Canada–as well as broader contexts, particularly as comparable institutions across contexts grapple with their own localized dilemmas of AI[3].

Notably, the study's findings will support pedagogical practices that prioritize teaching and learning; centre humans in decision-making processes; make ethical dilemmas explicit; model equity, diversity, and inclusion; and support innovative teaching, learning, and assessment. By providing current understandings of GenAI's implications for education, this review will equip educators with the knowledge to effectively and ethically leverage AI in educational settings. This comprehensive approach will ultimately enhance the learning experience for students across various institutions, ensuring that the integration of AI in education is done thoughtfully and responsibly, with a focus on improving educational outcomes and maintaining academic integrity.

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