

Pan-Canadian AI Consortium

Case Studies Collection
Quality of Teaching & Learning

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MAY 2026

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Table of Contents

Welcome **4**

Chapter One Introduction: Program and Course Learning Outcomes as Foundation for Meaningful AI Integration **7**

Case Study 1: Making Learning Expectations Explicit in Introductory Programming with AI in the Mix 8

Case Study 2: Advancing AI Literacy Through Intentional Program/Course Learning Outcomes and Curriculum Design Literature Review 12

Case Study 3: Advancing AI Literacy Through Intentional PLO/CLO and Curriculum Design Case Study 17

Chapter Two Introduction: Need for Institutional Culture Shift **22**

Case Study 4: Leading Institutional AI Adoption Through Culture and Clarity 23

Case Study 5: Higher Education AI Integration Progression Framework 27

Case Study 6: Institutional Responses to GenAI: Stepping Forward and Back with Courage and an Open Mind 33

Case Study 7: Case Study: A Polytechnic University's Response to Generative AI 42

Chapter Three Introduction: Assessment Redesign in Light of AI **49**

Case Study 8: Authentic Assessment at Scale 50

Case Study 9: Authentic AI Embedded Assessment Case Study 56

Case Study 10: Practicing the Hardest Conversations with AI Agents 62

Case Study 11: Leveraging NotebookLM as a Digital Portfolio for Entrepreneurship 75

Case Study 12: Adapting the PAIRR (Peer & AI Review + Reflection) Writing Framework 77

Welcome

This collection brings together case studies authored by post-secondary teaching and learning leaders from across Canada. Developed through the Pan-Canadian AI Consortium's Working Group on Quality of Teaching and Learning, this collection reflects a shared commitment to advancing educational quality during a period of significant pedagogical, technological, and organizational change.

The cases emerge from Canadian colleges, institutes, and polytechnics and address challenges related to foundational course and program learning outcomes, assessment, culture change, and the implications of generative artificial intelligence for teaching and learning. While these contexts differ, the case studies share a common orientation: they focus on what is happening right now in Canadia post-secondary classrooms and the impact of Gen AI on teaching and learning. Rather than presenting a "how-to" handbook or polished success stories, the authors surface tensions, trade-offs, and partial solutions that characterize the reality of being in higher education at this particular time in history.



Chapter Themes of Case Study Collection

When we began this journey as a Quality of Teaching and Learning working group, there was great discussion around how AI was positively and negatively impacting the quality of teaching and learning in Canadian colleges, institutes, and polytechnics. After wonderful conversation, three themes emerged and became the chapters of this collection:

CHAPTER 1: *Program and Course Learning Outcomes as Foundation for Meaningful AI Integration.*

It became apparent to us that to truly integrate AI into our teaching, AI needed to be reflected in our program and course learning outcomes. Without this foundation, changes to assessments or courses may not result in improving learning for students. Three case studies by Bowers, Taylor & Longmore, and Martin steeped in literature and lived experiences, showcase that having authentic and relevant outcomes is essential to the successful integration of AI.

CHAPTER 2: *Need for Institutional Culture Shift.*

After the realization that AI integration needed to happen at the program and course learning outcome level, if this was to become a reality, it became obvious that a culture shift in our institutions needed to happen. This shift must include supporting AI literacy for instructors and creating flexible frameworks and governance. In this chapter are three case studies by Grant, Wright and Southam & Martin. These authors share reflective accounts of instructors, leaders, and institutions purposefully making this culture shift.

CHAPTER 3: *Assessment Redesign in Light of AI.*

Redesigning assessments was the natural next step after working through foundational learning outcomes and culture shifting. While there are many resources available on how to redesign, our authors for this chapter share case studies on the messiness, failure, and success of such redesign. Khan, Newman, Samur, Kinelovskaya, and McIvor share real and current experiences and prototypes when seeking to redesign assessments in light of AI.

Guiding Principles for Collection

The following guiding principles, shared assumptions, values, and design stances synthesized by Co-Pilot from the working group documentation, underpin the case studies and supporting documents in this collection.

TRANSPARENCY BUILDS TRUST AND LEARNING

The case studies repeatedly emphasize transparency—about expectations, criteria, decision rationales, and limitations—as a foundational condition for quality. Whether redesigning assessment, aligning program learning outcomes, or shifting academic culture, clear communication about what is changing, why it is changing, and how judgment will be exercised is imperative.

ACADEMIC INTEGRITY IS A DESIGN RESPONSIBILITY

Rather than approaching academic integrity primarily through surveillance or enforcement, the cases frame integrity as an outcome of coherent course and program design. Assessment tasks that emphasize application, evaluation, and creativity are positioned as more robust responses to AI-enabled tools than detection-based approaches.

EQUITY IS CENTRAL TO QUALITY, NOT ADJACENT TO IT

Equity appears across the collection as an explicit consideration in decisions about learning outcomes and assessment formats. The cases highlight learner diversity and underscore that quality initiatives must avoid amplifying existing inequities.

CAPACITY BUILDING ENABLES SUSTAINABLE CHANGE

The cases consistently privilege capacity building over rapid compliance. Professional learning, shared design language, adaptable guides, and iterative support models are presented as more sustainable quality strategies than one-time workshops or standardized templates.

LEADERSHIP IN TEACHING AND LEARNING IS COLLECTIVE WORK

The collection affirms that meaningful improvement in teaching and learning is collective and distributed. Leaders operate alongside faculty, students, educational developers, and institutional partners.

Chapter One Introduction

Program and Course Learning Outcomes as Foundation for Meaningful AI Integration

Across post-secondary contexts, the emergence of Gen AI has led to many institutions and instructors scrambling to redesign AI "proof" assessments. Through our work in this consortium, the idea that our course learning outcomes and program learning outcomes are the foundation of our teaching and where AI needs to be considered. Redesigning individual assessments without revisiting course and program learning outcomes (CLOs and PLOs) addresses symptoms rather than root causes. The case studies and literature consistently demonstrate that assessments can only be made "AI-resilient" when they are anchored in learning outcomes that clearly articulate the level expected of students.

Many existing outcomes emphasize task completion or artifact production (e.g., written papers, reflections, and poster or video submissions) while leaving expectations for reasoning, judgment, and understanding implicit. Gen AI has made it much easier for these tasks to be offloaded, allowing students to meet surface-level outcome requirements without developing underlying competence. Simply modifying assignments such as adding handwritten assignments, oral defenses, or AI restrictions, cannot fully resolve this misalignment if the outcomes themselves remain at an insufficient cognitive or competency level.

Alignment of program-level outcomes in light of AI is particularly critical. Clearly articulated PLOs grounded in disciplinary practice and industry expectations provide a stable foundation for scaffolded CLOs and assessments that remain valid even as AI tools evolve. In this way, "AI-proofing" assessment is not achieved through detection or constraint, but through intentional outcome design that focuses on student learning and instructor teaching.

The following case studies put forward that learning outcomes must be recalibrated first, with outcomes defining what students must *demonstrate* regardless of tools. When CLOs and PLOs specify such dimensions explicitly, culture shifts and assessment redesign can be grounded in solid learning outcomes and become more coherent and sustainable.

Summary

Relevant, authentic PLOs and CLOs are the foundation for meaningful AI integration, strengthening learning, clarifying purpose, and addressing the root causes of AI related challenges in postsecondary education.

Chapter One: Case Study One -

Making Learning Expectations Explicit in Introductory Programming with AI in the Mix

Institution: Holland College
Prepared by: Don Bowers

Context Snapshot

Holland College is a publicly funded Canadian college offering applied diploma programs. This case focuses on CPRG-1000: Basics of Programming, a first-year course in the Computer Networking Technology program.
The course introduces foundational programming concepts, including variables, conditionals, loops, strings, lists, file handling, and basic functions. Students are typically in their first semester and include a mix of recent high school graduates, mature learners, and international students. There is a wide variation in prior programming experience and comfort with technical language.

The course emphasizes applied learning through labs and structured assignments. Instruction is face-to-face with dedicated lab time. Assessment includes both coding and written components, with increasing emphasis on reasoning.

The Problem / Opportunity

Students were able to produce correct coding outputs without demonstrating understanding.
This was not new. Some students had already been completing programming tasks by pattern-matching or copying examples. However, generative AI made this easier and more widespread by allowing students to generate working code quickly, often without engaging in the reasoning required to construct it.

This exposed a gap in course design and assessment. Learning outcomes described tasks such as writing programs or using control structures, but did not clearly define the level of understanding required to complete them. Previously, this level of performance was indirectly enforced by environmental constraints such as time, effort, and limited access to external tools. As generative AI removed these constraints, the underlying expectations became unclear. As a result:

- Correct answers were not reliable evidence of learning
- Students could meet requirements without developing foundational skills
- Grading became more ambiguous when reasoning was not visible

At that point, it was clear that “working code” wasn’t good enough anymore, so the assessment had to shift toward showing actual understanding of what the code was doing.

The Exploratory Space

Three approaches were considered:

1. Restrict AI use:
Difficult to enforce and did not address unclear expectations

2. Maintain existing assessments:
Risked further weakening the validity of results

3. Redesign assessment to require visible thinking:
Focused on making student reasoning explicit

The third approach was selected. The decision was not to control tool use, but to ensure that, regardless of tools, students had to demonstrate understanding. In practice, that meant changing what we were actually looking for in their work. This change also required clarifying what the outcomes were actually asking students to demonstrate. Rather than focusing on task completion (or product production), the redesign focused on making the expected level of student understanding (including judgment) explicit and observable.

The Approach Taken

Assessment was redesigned to require students to make their thinking visible. Course learning outcomes were reinterpreted to clarify the level of understanding required. For example, outcomes that required students to "apply" programming concepts were treated as requiring students to predict, trace, and explain program behaviour. This brought the assessment back in line with what we actually wanted students to understand in the first place.

STRUCTURED REASONING TASKS

A consistent "Prediction → Trace → Explain" model was introduced, where students first anticipate program output, then step through execution line by line, and finally explain how and why the result occurs. This shifted the focus away from just getting code to work and toward understanding how it actually behaves.

REDUCED RELIANCE ON EXECUTION

Some assessments were designed as non-executable or paper-based tasks. This made trial-and-error much harder and required students to rely on reasoning rather than runtime feedback or context-based assistance in coding software.

ALIGNMENT TO EXPECTATIONS

Course expectations were clarified through assignment instructions, grading criteria, and in-class modelling, with consistent examples of what a complete explanation looks like and how it would be evaluated.

FINAL PRACTICAL ASSESSMENT DESIGN

The final practical emphasized structured problem-solving, clear explanation of logic, and a constrained use of external tools, with students assessed on their ability to apply concepts and explain their reasoning rather than simply produce working solutions.

COMMUNICATION WITH STUDENTS

Students were explicitly told that correct answers alone were not enough, that explanations would carry the most weight, and that demonstrating understanding was required for full marks, which helped align their effort with what was actually being assessed.

What Happened: Outcomes & Evidence

Learning Indicators

- In a few cases, students who had full marks on earlier coding tasks couldn't walk through what their own program was doing. That was a bit of a wake-up call!
- It became much easier to identify where students were actually getting stuck

Student Behaviour

- Initial resistance showed up pretty quickly once students couldn't rely on running the code to check themselves
- Over time, students shifted focus toward understanding rather than completion

Instructor Reflection

- Grading became more consistent and less ambiguous
- Explanations provided clearer evidence than outputs
- It also forced much clearer expectations upfront

Evidence Snapshot

Sample Task

Without running the code, predict the output of the program. Trace the execution step-by-step. Explain how the final value is produced.

Grading Emphasis

- Correct output: minimal weighting
- Trace accuracy: moderate weighting
- Explanation of logic: highest weighting

Ongoing Challenges

- Students accustomed to tool-assisted workflows required adjustment
- Managing cognitive load for beginners remained important
- Expectations were not always aligned across other courses in the program
- Balancing real-world, tool-assisted environments with tracing code on paper seems 'old-school'



What I Would Do Differently

- I would introduce reasoning tasks earlier to reduce initial friction
- Include low-stakes mock practical assessments to calibrate expectations
- Add more staged checkpoints to capture thinking over time
- Provide additional examples of strong explanations

Recommendations

For Instructors

- Define learning outcomes in terms of the level of human performance required, not just task completion. The level of human performance is really about the kind of thinking a student must demonstrate, not the output they can produce.
- Design assessments that require students to demonstrate understanding through observable reasoning (prediction, tracing, explanation)
- Look at your verbs. If they only describe a task, they're probably not enough anymore
- Prioritize explanation, interpretation, and justification as primary evidence of learning

For Programs

- Review learning outcomes to ensure they specify the expected depth of understanding and application, not just the task
- Align outcomes, assessment, and instruction around demonstrated competency rather than produced artifacts
- Be cautious with outcomes that can be met through generated responses without showing real understanding
- Establish shared expectations across courses for what constitutes valid evidence of student learning

For Teaching and Learning Support

- Support instructors in identifying where outcomes rely on implicit assumptions about effort, environment, or tool limitations
- Provide models of assessment that capture student reasoning and decision-making processes
- Facilitate conversations on how AI changes the relationship between task completion and demonstrated learning
- Encourage outcome and assessment design that reflects authentic, context-based performance expectations

Closing Note

This case highlights the need to make expectations for human performance explicit at the outcome level. In AI-assisted learning environments, clearly defining what students must understand, not just what they can produce, is critical to maintaining the validity of assessment.



Chapter One: Case Study Two -

Advancing AI Literacy Through Intentional Program/Course Learning Outcomes and Curriculum Design Literature Review

Institution: Georgian College and Langara College
Prepared by: Dr. Anne-Liisa Longmore and Alexandra Sumar

According to the World Economic Forum Future of Jobs report 2025, technological advancements, including generative artificial intelligence (AI), are expected to continue to transform business and industries globally for the foreseeable future. This disruption and evolution is expected to fundamentally reshape how we work, learn and live (World Economic Forum, 2025) and is fueling the growing expectation to meaningfully integrate AI and big data literacy along with other 21st century competencies such as creative thinking, resilience, flexibility, and lifelong learning (among others) into learning contexts (Biagini, 2025; World Economic Forum, 2025). The Lightcast Global Skills Outlook Report (2024) noted this expectation from industry and employers is growing beyond data-specific roles and is emerging with greater frequency in non-technical fields and professions as well. Studies indicate that there is growing recognition that employees and learners alike engage with AI in various contexts without knowledge or understanding of the ethics, biases, societal impact of the technology (Biagini, 2025). As a result, the demand for AI literacy is increasing across multiple fields of practice for learners in post-secondary programs to possess and demonstrate AI literacy upon graduation (Biagini, 2025; Figueroa de la Fuente & Farhadian, 2025; Hong, 2025; Jacques, Moss, & Garger, 2024; Liang, Stephens & Brown, 2025). According to the University of Calgary (2026), An AI-literate person can:

- Understand what AI is and the basic principles behind how it works.
- Evaluate AI outputs for accuracy, bias, and credibility.
- Use AI tools strategically to enhance academic, professional, and creative work.
- Reflect on the ethical, legal, and societal implications of AI use.
- Adapt their approach depending on the task, audience, and institutional policies

AI literacy involves recognizing that AI is not a neutral technology but that it is shaped by human decisions about data, algorithms, and goals. This means evaluating both the benefits and the potential harms of using AI in the context you are using it (para 3).

Recommendations are being made to broaden the knowledge, skills and attitudes (competency) development beyond the technical or discipline-specific skills in post-secondary education to include AI literacy in addition to critical reflection, communications, creativity, complex problem-solving, emotional intelligence, among others (Figueroa de la Fuente & Farhadian ,2025; Jacques, Moss, & Garger, 2024; Liang, Stephens & Brown, 2025). However, current technical and discipline-specific knowledge-acquisition framing of courses and programs follows a linear framework and does not fully align with competency-based education principles, nor is it adequate to evolve with the rapid-paced evolution of AI and other technological advancements (Hong, 2025).

While review of AI-related literature illustrates a growing body of work in areas such as academic policy, ethics, individual teaching strategies (including assessment design and detection) and personalized learning for students, there are limited studies exploring the educational ecosystem, including curriculum and program design from a holistic perspective (Figueroa de la Fuente & Farhadian ,2025; Hong, 2025; Jacques, Moss, & Garger, 2024; Liang, Stephens & Brown, 2025). To add complexity, in their study exploring AI literacy and curriculum planning in an Agricultural Sciences program, Kymälainen, Cräutlien, Elo, Galambosi, Honkanen, Pietikäinen and Södervic (2024) noted that AI literacy is a complex concept to explore, with very little alignment on a common definition. Kymälainen et al., (2024) and Hong (2025) both note that AI literacy is multi-dimensional including knowledge and skills about AI and its application, ethics, critical assessment and evaluation as well as the metacognitive elements, thus making it difficult to cultivate AI literacy through one policy, course or a singular element or teaching strategy within a course. It requires an interconnected and interdependent framework that is scaffolded across the field of practice and reflects industry needs. In developing their AI literacy framework, Kymälainen et al. (2024) recommended that any program area considering the inclusion of AI literacy into their learning outcomes, must contextualize it to the philosophy and practice perspectives within the knowledge domain of that field and discipline. Skills should be carefully analyzed and mapped across the curriculum and linked to externally validated occupational skills and competencies indicated by the specific industry (Hong, 2025; Kymälainen et al., 2024).

Building on the works of Ng et al. (2023) and others, Kymälainen et al.(2024) created a framework of AI literacy (see Figure 1 below).

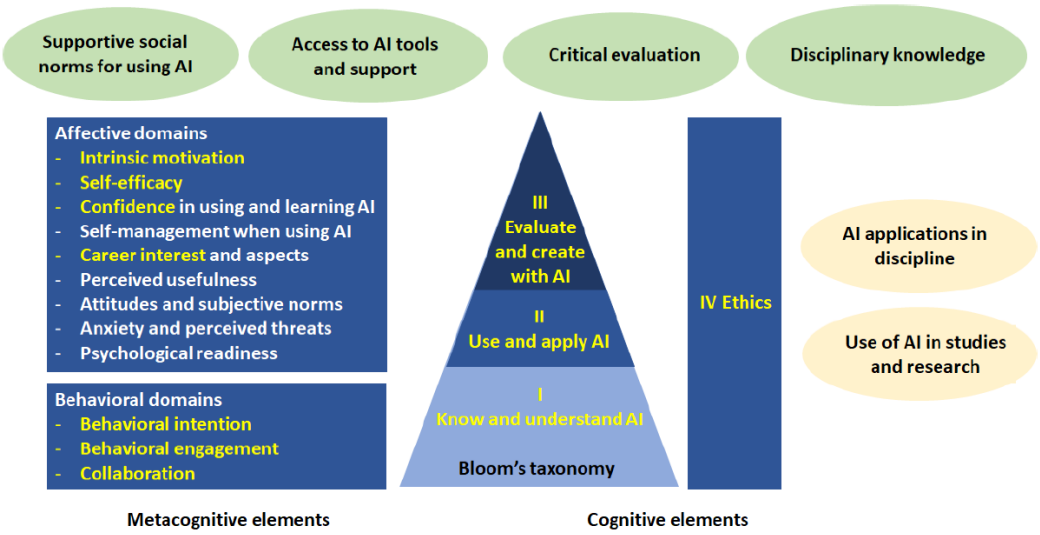


Figure 1: Framework of AI Literacy and Related Aspects for Curriculum Planning, Reproduced from Kymälainen et al., (2024)

Kymälainen et al. (2024) applied the AI Literacy Framework to guide faculty as they designed a four-year degree program. Through a consultation process they intentionally applied five categories of AI learning put forth by Southworth et al. (2023) and ensured AI literacy and training in the use of AI were integrated across the curriculum. For the purposes of this case study, University of Calgary's (2026) working description of an AI-literate person will be used. An AI-literate person can:

- Understand what AI is and the basic principles behind how it works.
- Evaluate AI outputs for accuracy, bias, and credibility.
- Use AI tools strategically to enhance academic, professional, and creative work.
- Reflect on the ethical, legal, and societal implications of AI use.
- Adapt their approach depending on the task, audience, and institutional policies.

University of Calgary (2026) further states, "AI literacy involves recognizing that AI is not a neutral technology but that it is shaped by human decisions about data, algorithms, and goals. This means evaluating both the benefits and the potential harms of using AI in the context you are using it" (para 4).

Kymälainen et al. (2024) scaffolded AI literacy development and learning throughout the four-year program by ensuring that the aims, learning outcomes, learning strategies and assessment all clearly aligned using a spreadsheet to guide the decision-making process. From a program delivery perspective, intentional teaching and learning and assessment strategies that support the development of AI literacy were adopted such as discovery and inquiry-based learning, collaborative learning, problem or project-based learning among others. Assessment is clearly linked to the course learning outcomes.

In a separate study, and building on the UNESCO AI competency framework for students (2024), Hong (2025) similarly suggests AI literacy development be fostered through integrating careful competency mapping, scaffolded skill building and authentic assessment practices that reflect real-world AI application. See Figure 2 below.

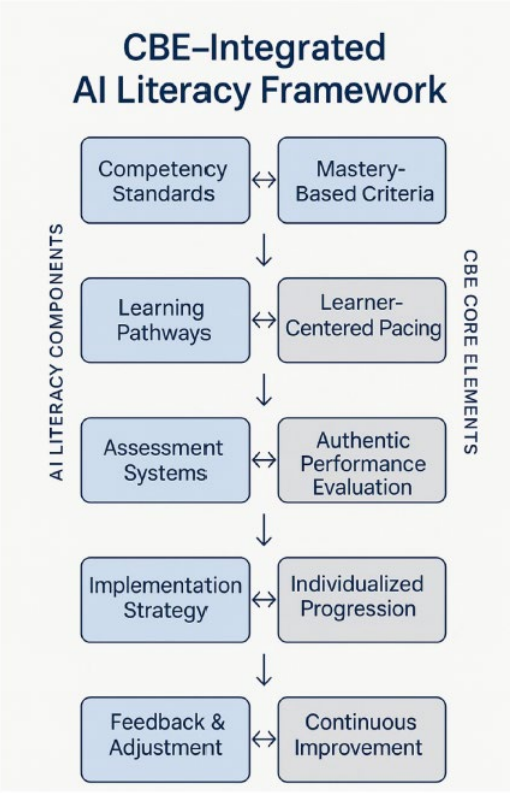


Figure 2: AI literacy competency-based system architecture.

Reproduced from L. Hong...



In Hong's (2025) framework, the following four domains of AI literacy were explored:

1. Cognitive understanding of AI concepts
2. Technical proficiency in AI tools and applications
3. Practical implementation capabilities
4. Awareness of ethical considerations in AI use.

The key principles are progressive advancement, practice-oriented learning and authentic formative and summative assessment design (Hong, 2025). Progressive advancement is where an AI literacy competency baseline level standard is established in consultation with industry experts and using a backwards design framework, developmental learning levels are intentionally built to ensure knowledge and skills are carefully scaffolded from the start of a program through to graduation so as to provide learners with opportunity to continue develop and grow from one level to the next.

Once the disciplinary expectations for AI literacy are established for a program, effective design requires the drafting of clear program-level learning outcomes that define the knowledge, skills and abilities that students will be able to demonstrate upon successful completion of all of the courses within the program. The course learning outcomes are articulated after and are informed by the program-level learning outcomes. From a competency development perspective these outcomes are progressively mapped and scaffolded to higher levels of learning. According to van Kollenburg (2025), decisions and design for AI literacy should be constructively aligned with learning outcomes and aligned with teaching strategies, and assessments (see Figure 3 below).

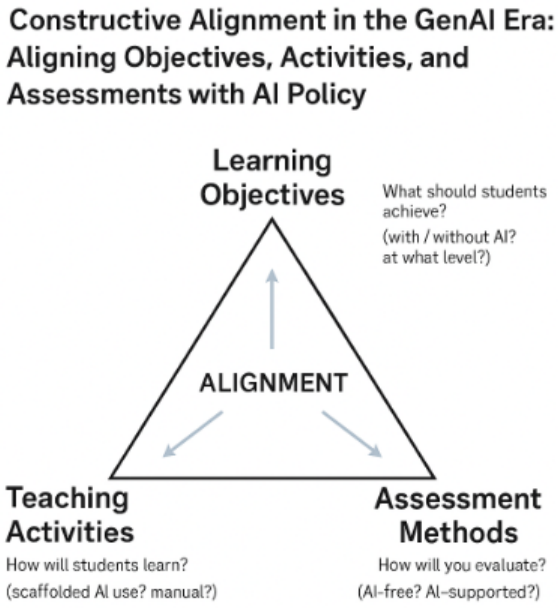


Figure 3: Representation of constructive alignment. Reproduced from van Kollenburg (2025)...

Evaluating Bloom's Taxonomy in An AI-Transformed Higher Education Landscape

While these frameworks emphasize the importance of intentional, scaffolded, and competency-based approaches to developing AI literacy, they also raise important questions about how learning outcomes themselves are conceptualized and articulated. In many post-secondary contexts, the development of program and course learning outcomes continues to be guided by Bloom's taxonomy and its pyramid model of cognitive processes (cite).

In *Small Teaching* (2016), James M. Lang, a prominent voice in higher education pedagogy, cautions against dismissing Bloom's taxonomy in response to emerging technologies. He argues that so-called "lower-order" cognitive skills, such as remembering, remain foundational to learning and cannot simply be outsourced to tools like search engines. Students require a base of knowledge in order to engage in deeper forms of thinking. From this perspective, Bloom's taxonomy continues to offer a useful lens for understanding

cognitive development, even in technology-rich learning environments (Lang, 2016, p. 14-15). More recently, in the context of generative AI, Lang has suggested that educators can leverage these tools to support deeper learning by including variety, transparency, sequencing and reflection into their assignments beyond simple content generation toward evaluation and creation (Lang, 2024).

However, while Bloom's taxonomy has been critiqued for its rigid, hierarchical structure (cite), particularly the assumption that learning progresses in a linear fashion, these critiques take on renewed significance in AI transformed learning contexts. As AI systems increasingly perform tasks associated with higher-order cognitive processes, such as analysis and generation, the distinctions embedded within Bloom's hierarchy become less clear. This has prompted renewed attention to alternative learning frameworks that may better account for the iterative and practice-oriented nature of learning in AI transformed learning environments. The following section outlines new frameworks that build on Bloom's or provide new alternatives entirely and their implications for curriculum and learning outcome design.

RETHINKING BLOOM'S AND ALTERNATIVE TAXONOMIES

Bloom's Taxonomy Revisited – Artificial Intelligence Tools – Faculty Support | Oregon State Ecampus | OSU Degrees Online

While Bloom's Taxonomy remains a common reference point for aligning learning outcomes, activities, and assessment in higher education, recent work has begun to re-examine its application in the context of generative AI. In this adapted model by the University of Oregon, Bloom's is used not as a fixed model but as a reflective tool to interrogate how learning design may need to evolve in response to AI-mediated practices. This approach highlights the need to revisit assumptions about what constitutes meaningful learning and to explore opportunities for integrating generative AI in ways that support, rather than replace, student thinking. It also underscores the importance of attending to student perspectives in the redesign of AI-informed learning environments.

Inverted Bloom's for the Age of AI - by Michelle Kassorla
Michelle Kassorla and Eugenia Novokshanova, scholars from East Georgia State College, have proposed an "inverted" interpretation of Bloom's taxonomy, in which the traditional hierarchy of cognitive processes is effectively reversed. In this model, students may begin by *creating* outputs using AI tools with limited understanding, then move through stages of evaluation and analysis that may include AI. As learners gain greater agency, they begin to apply, understand, and ultimately internalize knowledge with decreasing reliance on AI.

This reframing challenges the assumption that learning progresses linearly from lower- to higher-order thinking and instead suggests that AI enables early access to complex outputs without corresponding depth of understanding. As a result, the role of instruction shifts toward intentionally designing opportunities for reflection and "productive friction" to support meaningful learning.

The UnBlooms™ model: A Problem-Centered Framework for Learning Design in the AI Era
Beyond Bloom: A Radial Taxonomy for Microcredentials | EDUCAUSE Review

Chapter One: Case Study Three

Advancing AI Literacy Through Intentional PLO/CLO and Curriculum Design Case Study

Institution: Georgian College
Prepared by: Susan Salt Taylor, Program Development and Renewal Consultant and Dr. Anne-Liisa Longmore, Dean

Context Snapshot

Georgian College, located in Central Ontario, is known for working closely with industry and community partners to collaboratively create innovative learning experiences for its students culminating in graduating emerging leaders with creative mindsets who can transform their workplaces and communities. As of June, 2025, Georgian has annual enrolment of approximately 13,000 full-time students, with over 120,000 alumni across 130 programs.

In 2025, Georgian College's two-year Business – Entrepreneurship Diploma program embarked on a comprehensive program review that included the incorporation of AI into its curriculum along with enhanced alignment to the college's institutional priorities. One of the key commitments of Georgian College's 2025-30 strategic plan is "transformative education", and one of the foundational areas of focus that is woven through all the key commitments is Changemaking. [1] These pillars are underpinned by a strong relationship with industry partners to ensure that programs are current.

Innovation and entrepreneurial outcomes are embedded in all of Georgian's more than 130 academic programs, with support for students and community members offered through the Henry Bernick Entrepreneurship Centre and the Centre for Changemaking and Social Innovation. By the nature of the program, these outcomes are a focal point in the Business – Entrepreneurship diploma. The enhancement of technological outcomes, and AI in particular, align with both the college's priorities and the clear evidence provided by the literature related to AI literacy and its application within the field.

The Catalytic Problem / Trigger / Opportunity / Exploration

The catalytic trigger and opportunity centre on enhancing program currency by including 21st century skill of AI literacy, along with applications of AI in the field.

In Fall 2025, the Business – Entrepreneurship diploma began its 5-year comprehensive program renewal process. During the consultation phase, the program consulted with its Program Advisory Committee (PAC), comprised of local industry experts in the field, to seek input based on any gaps they may see in the program, and share industry changes on the horizon that may need to be considered in the renewed curriculum. The PAC identified the exigency of incorporating AI as a means of not merely maintaining currency but future-proofing the curriculum to ensure that students are adequately prepared for the workplace upon graduation. Other

industry experts independently consulted by the program concurred with this assessment, including those at Georgian College's Henry Bernick Entrepreneurship centre, and the Sandbox Centre, a regional innovation hub located in downtown Barrie.

The Business – Entrepreneurship program faculty all agreed that including industry perspectives in the curriculum exploration, along with including AI in an intentional and meaningful way was important. This approach is supported by the Lightcast Global Skills Outlook Report (2024) [2], Hong (2025) [3], and Kymälainen et al (2024) [4].

The Decision or Exploratory Space

With the identification of the need to incorporate AI into the curriculum, the exploration began to determine the essence of including "AI in the curriculum". There were three broad concepts for discussion: (1) AI as a mechanism for academic misconduct, (2) AI literacy, and (3) applied AI. One of the anticipated risks identified was the potential confusion between the three and a need for initial clarity during discussions. This discussion aligned with Kymälainen et al. (2024) [5] observations that AI literacy is a complex concept to explore, with very little agreement on a common definition.

At the time, the institution was still in the process of developing policies related to AI as a mechanism for academic misconduct. The program's approach primarily explored the inclusion of two concepts: AI literacy (with a priority on ethics), and applied AI (that is, AI in entrepreneurship). The consideration was linked to the initial impetus for including AI through industry feedback. The exploration revolved around a focus of AI as a workplace tool with AI literacy alongside. Teaching students how to intentionally and ethically use AI as a tool, rather than viewing it as a decision-maker, was deemed to be the best way to future-proof the embedding of AI in the curriculum.

The exploration continued with how to incorporate AI skills development in the new curriculum. Questions considered included, How does a program future-proof itself with such a fast-moving shift as AI? Should this be a standalone course, or outcomes embedded throughout the program's other courses and semesters, or both? Should there be a separation of AI literacy and applied AI, or should these be dealt with in tandem? By the time the new curriculum launches in 18 months will the decisions of today still make sense?

Another consideration was which faculty would develop and teach a potential new course about AI. Faculty within the program did not consider themselves to be AI subject-matter experts. Consequently, AI subject-matter experts were engaged in consultation during the development of the related aspects of the curriculum. There were discussions around who would be qualified to teach AI literacy. This evolved into the consideration of the point at which the Business – Entrepreneurship program faculty would need to view themselves "AI in entrepreneurship" subject-matter experts as part of the evolution of the industry.

In examining the risks, the three largest were the fast-moving nature of AI and the possible future redundancies of some of the approaches being taken, along with the faculty expertise within the program. These were counter-balanced with the absolute necessity to include AI and the risks of not doing so.

The Approach Taken

By its definition, "entrepreneurship" is underpinned by innovation, and in its continued exploration the program faculty determined that the importance of AI innovation warranted an additional program-level learning outcome. The following broad technological program learning outcome (PLO) was added that would capture AI as part of the title modifier ("Entrepreneurship") of the provincial standard. *Harness AI-driven tools, data analytics, and emerging digital technologies to create innovative business models, automate workflows, and transform insights into growth strategies.* The PLO was reviewed and validated by Credential Validation Services in January 2026

A cross-portfolio approach was taken to leverage existing AI subject-matter experts within the college. The coordinator of the Business - Entrepreneurship program reached out to the Computer Studies team within the Design and Visual Arts portfolio for collaboration and support.

Consultations led to the conclusion that initially an AI-focused course would be developed to address both AI literacy and ways in which AI could be applied to entrepreneurship. Future states of the program would continue to develop ways of embedding AI components into existing courses.

In the new standalone course, *ENTR 2021: Applied AI for Business Innovation*, students will discuss how AI is reshaping the ways in which businesses operate, innovate, and compete. Students will develop and practice skills to leverage AI tools for enhanced efficiency, creativity, and data-driven decision-making, with an emphasis on ethical and responsible AI use. They will apply cutting-edge technologies to real-world entrepreneurial challenges and learn to integrate AI solutions into business strategies, streamline operations, and drive innovation.

The scaffolding of learning of the AI program-level outcome has initially been focused within the new course, with a recognition that this will evolve as the inclusion of AI concepts in the program change with time. The course's learning outcomes are aligned with the University of Calgary's 2026 [6] working description of an AI-literate person. The course covers foundational AI concepts (University of Calgary's "understand what AI is and the basic principles behind how it works"), the evaluation of ethical and responsible AI adoption by addressing biases, transparency and compliance ("evaluate AI outputs for accuracy, bias, and credibility" and "reflect on ethical, legal, and societal implications of AI use"), and the use and application of AI tools and workflows, including interpretations to support evidence-based business decisions and strategic recommendations ("use AI tools strategically to enhance academic, professional, and creative work" and "adapt their approach depending on the task, audience, and institutional policies"). Bloom's taxonomy was used in the determination of the verbs for each of the six course learning outcomes, in order to intentionally map and scaffold the learning within the course from foundational understanding to application and interpretation.

As course development evolved, the Associate Dean of Business identified it as a course that would be well-suited for other programs within the portfolio. To ensure applicability across the portfolio, the course was developed generally enough to be used by other programs while still capturing the innovative elements of entrepreneurship. While this was not an intentional goal at the beginning of development, this evolution ensured that the course remained broad enough to support future-proofing and the sharing of expertise and resources from an operational standpoint.

What Happened: Outcomes and Evidence

Program renewal work was completed in early 2026 and following the college's process for renewed curriculum, program changes were presented to Georgian's Academic Council in February 2026 for approval. The program renewal was approved as presented. Interestingly, the new AI course generated curiosity and questions from Academic Council members, particularly related to ethics and the expertise of potential faculty who would be attached to the course.

While the AI course outline has been written, and approved, the next steps include more in-depth development of teaching strategies and assessments, with support from the Centre for Teaching and Learning (CTL)'s instructional designers. In tandem with course development, faculty will be encouraged to engage in Georgian's Faculty Competency Framework which includes badges related to Changemaker and Digital Navigator, and CTL's curated resources and offerings related to AI. This process will continue in the coming months in preparation for the first teaching of the course in Fall 2027.

The exploration that occurred as part of this program's renewal has dovetailed into the consultation process facilitated by the Office of Academic Quality (OAQ). How to incorporate AI literacy into the curriculum will be included in OAQ's Consultation Guide for program development and comprehensive renewals. This includes guiding questions, sample learning outcomes, resources, and contact information for those within the college with relevant expertise. OAQ will be increasingly intentional in facilitating conversation about AI and encouraging programs to actively engage their PACs for input on specific ways in which AI is being used in their industries.

Evidence of success for this initiative will provide valuable insight into its impact and sustainability. In the same way as integrating AI into the curriculum is both difficult to define and continually evolving, metrics for measuring its success may require a holistic approach. At Georgian, data will be drawn from student and Program Advisory Committee program feedback surveys, the Ontario College Student Experience Survey, and the Academic Outcomes dashboard. In addition, Georgian's Annual Program Quality Review (APQR) process will capture qualitative data in questions such as 1.6 *In what ways are you maintaining currency in the curriculum?* and 1.12 *How does the program develop a student's soft/transferable skills and non-core competencies (ie Essential Employability Skills; 21st Century competencies?* [7]

What They'd Do Differently

The implementation of the curriculum is still in process with the renewed curriculum coming into effect approximately 18 months after the key recommendations are identified and presented to the college's Academic Council. As such many of the current thoughts are projections based on the work completed to date. Upon reflecting on the process of enhancing the AI components of the program, the Business – Entrepreneurship faculty identified some future points of discussion.

In future iterations of the course the program hopes to continue to enhance the clarity of what AI looks like in the curriculum. Further examination of the intersection of AI literacy and AI in the industry (in this case, entrepreneurship) will drive further incorporation of AI concepts throughout the curriculum.

On the other hand, there is a recognition that this conversation is in a transitional space. In a way the inclusion of a new standalone AI course into the curriculum is a bridge between the relative infancy of AI

and crossing over towards its eventual full adoption. The expectation is that at a future point in time, AI will be so embedded in the industry that there will be more fully developed "AI in entrepreneurship" expectations.

This leads to the discussion of current subject-matter expertise. In this specific case, there was reliance on the capacity and willingness of a faculty member from one portfolio to support course development in a program in another. In addition, there is still ambiguity around who will teach the course. The eventual expectation is that AI will be engrained in the industry and by extension the entrepreneurship faculty will by default become "AI in entrepreneurship" subject-matter experts. In the meantime, there will be a need for cross-portfolio collaboration and faculty development. Even as AI becomes enmeshed in all aspects of business, the need for AI literacy will not disappear.

Another future consideration is the potential resistance to the change in culture among faculty and students. While early adopters have become proficient in the ways in which AI are influencing their industry, there still exists varying degrees to which faculty have embraced how AI is showing up in their field. Although there is an assumption that this is likely to level out, there is the additional cultural shift of faculty's role in AI literacy in general. There is also a misconception that those students who are digital natives enter post-secondary education with a highly developed sense of computer literacy, whereas the reality is that some students come out of high school requiring support for basic computer functions. Regardless of their pathway into post-secondary education, some students' exposure to AI may have only been in an academic integrity context, underscoring the need for comprehensive AI literacy and how it applies in industry. This includes the risks of allowing AI to complete tasks and make decisions on their behalf. To avoid these culture-change barriers, clear definitions, messaging, and support will be necessary.

Recommendations

As an interim measure, AI subject-matter experts should be attached to new program development and programs undergoing comprehensive renewals. This will facilitate the conversations around defining the various aspects of AI, best practices for integrating into the curriculum, and clarity on the importance of both AI in the industry, and AI literacy.

In order to maintain currency, programs should develop regular engagement with industry. This informs the incorporation of new trends on the horizon into the curriculum, including AI and how it is being used in the workplace.

Any AI elements being infused into the curriculum should be broad enough to stand the test of time. With renewed curriculum launching 18 months after changes are determined, and an element as fast-paced as AI, there is a real risk that the planned incorporation strategies are outdated before the curriculum is implemented. Both AI subject-matter experts and industry-specific expertise will be best positioned to future-proof any AI integration into the curriculum.

Communication and support of both faculty and students will be critical. Faculty should be encouraged to explore the ways in which AI is being used in their industry. Business – Entrepreneurship students should understand the liabilities – including to their business's reputation and finances – of ignoring the responsible use of AI, while also harnessing its capabilities to enhance their future businesses.

Chapter Two Introduction

Need for Institutional Culture Shift

Initial institutional responses to artificial intelligence (AI) in post-secondary education were frequently framed through academic integrity, emphasizing detection, control, and prevention of misuse. Faculty responses revealed deeper uncertainty—not only about student conduct, but about instructional identity, disciplinary expertise, and the evolving purpose of higher education. As AI intersects with an already complex landscape of institutional change, a cultural shift is required—one that moves beyond enforcement toward shared meaning-making, trust, and collective responsibility.

This shift requires repositioning core educational priorities. Rather than centering decisions on the capabilities or limitations of AI tools, institutions must reaffirm the primacy of program and course learning outcomes. The critical question is no longer whether AI is permitted, but what constitutes meaningful evidence of learning in its presence. Where existing outcomes remain relevant, assessment practices must evolve to ensure alignment within an AI-mediated context. Where outcomes are destabilized, they must be reconsidered and, where necessary, redefined. This reorientation signals a move from reactive policymaking to principled, outcomes-driven design.

A second dimension of this cultural shift lies in recognizing the importance of disciplinary context. AI integration cannot be approached as a universal or standardized solution. Each field brings distinct methodologies and criteria for evaluating knowledge. As a result, meaningful adaptation must emerge from within disciplines, supported by institutional structures that encourage dialogue about credibility, authorship, and the nature of expertise. This requires a shift from top-down guidance toward distributed, collaborative leadership.

The diversity of instructor perspectives further underscores the need for cultural transformation. Responses to AI range from resistance to rapid adoption, often shaped by varying levels of confidence, experience, and ethical consideration. A culture shift must therefore create conditions for engagement across this spectrum. This includes investing in AI literacy, establishing clear but flexible guardrails, and fostering a shared language that enables educators to articulate and justify pedagogical choices. Such an approach prioritizes reflective practice over compliance and supports gradual, informed change.

Finally, students are not passive participants in this transition. Their concerns regarding ethics, privacy, and societal impact highlight the need for a more holistic approach to AI integration. Preparing learners for an AI-enabled world requires not only technical familiarity, but critical awareness and responsible use. In this context, assessment and curriculum design must position students as active contributors to the evolving educational landscape.

Summary

Shifting institutional culture in light of AI requires rethinking and embracing PLO and CLO, engaging diverse instructor beliefs, clarifying disciplinary values, addressing student concerns, and fostering shared institutional philosophies that support evolving teaching practices

Chapter Two: Case Study Four

Leading Institutional AI Adoption Through Culture and Clarity

Institution: NAIT
Prepared by: Josalynne Balajadia

Context Snapshot

As a polytechnic institution, the Northern Alberta Institute of Technology (NAIT) serves a large and diverse learner population through a broad portfolio of applied, technical, and professional programs. NAIT enrolls approximately 14,000 students in credit programs, with an additional 8,700 registered apprentices and 14,000 learners in non-credit and continuing education offerings. NAIT employs approximately 2,500 staff, with over 1000 academic staff members.

NAIT has faced pressures common across the post-secondary sector: rapid generative AI advancement, heightened concerns around academic integrity and assessment design, increasing demand for staff productivity tools, and the need to prepare graduates for AI-augmented workplaces. In response, NAIT applied a strategy that focused on institution-wide cultural readiness. With thousands of employees, a large and diverse student population, and wide-ranging programs, successful AI adoption required a shared language, clear governance, and strong cross-functional collaboration. This case study examines how NAIT supported a measurable culture shift around AI. From early experimentation and uncertainty toward more confident, responsible, and purpose-driven use of AI tools across teaching, learning, and operational contexts.

The Catalytic Problem / Trigger/ Opportunity/ Exploration

As AI tools started to show up more visibly in daily work, questions followed. Staff across academic and operational roles began asking what AI could be used for, whether it was allowed, and where the boundaries were. Conversations ranged from teaching and assessment to productivity, ethics, privacy, and data security.

Some jumped in early by experimenting, sharing tips, and becoming informal go-to experts. Others were more cautious, or openly hesitant. In many cases, early adopters were moving faster than policy creation. At the same time, there were concerns among staff. Some worried AI might replace parts of their roles, undermine the value of expertise, or lower expectations for the quality of work and student submissions. These concerns reflected a deep commitment to quality and accountability.

Ad hoc adoption wasn't enough. With curiosity growing, expertise unevenly distributed, and questions continuing to surface, there was a clear opportunity to take a more coordinated, institution-wide approach that could build shared understanding, increase confidence, and support responsible, consistent AI use across NAIT.

The Decision or Exploratory Space

As NAIT explored institute-wide AI initiatives, several considerations shaped how adoption was approached.

Mandatory AI training	Prescriptive AI Usage	Quality Student Experience
While mandatory training was discussed, NAIT chose not to prioritize a universal requirement. Staff turnover, varied roles, and differing levels of familiarity with AI meant employees were at very different points in their learning journeys. Introducing mandatory training risked prioritizing speed over comprehension. Instead, emphasis was placed on ensuring clear foundations before expecting widespread adoption.	A mandatory or prescriptive approach to AI usage risked emphasizing output at the expense of broader considerations. Instead, aligning AI initiatives with existing responsible-use procedures helped position AI as a tool that required judgment rather than obligation.	Instructors and staff play a critical role in modeling professional practices for students. Institute-wide AI initiatives needed to reinforce, rather than dilute, expectations around quality, diligence, and accountability. By emphasizing thoughtful and transparent AI use, staff have the choice to be role models demonstrating when and how AI can be responsibly integrated into academic and operational work.

The Approach Taken

In response to growing interest in AI and the need for a coordinated culture shift, NAIT adopted an approach that balanced access, responsibility, and flexibility. Rather than relying on a single mandate or tool rollout, the approach combined policy, enablement, professional learning, and governance to support thoughtful adoption across diverse roles and readiness levels.

A foundational step was the implementation of a formal AI acceptable use and responsible use framework, which established clear boundaries for how AI could be used within the institution. This policy clarified expectations related to ethics, privacy, and data protection. By setting guardrails early, NAIT enabled experimentation while reinforcing responsibility as a shared institutional value.

To build baseline AI literacy, NAIT introduced two foundational AI courses tailored to different staff roles. Rather than making these courses mandatory, the target was an 80% completion rate across the institute. This acknowledged differences in readiness, role relevance, and workload. Framing the courses as an entry point, rather than a compliance requirement, helped reduce resistance and reinforced learning as an ongoing process. This approach was reinforced by embedding AI professional development into existing, institute-wide PD events instead of treating AI as a standalone or niche topic. Doing so normalized AI as part of everyday work at NAIT and reduced the perception that AI adoption was limited to technical teams or early adopters. Sessions focused on practical, role-relevant uses of AI and responsible practices, helping staff see how AI could fit naturally within their existing teaching and work routines.

In-person staff training further supported this shift by centering on enterprise-approved tools and resources. By focusing on solutions already reviewed and supported by the institution, these sessions reduced reliance on

untested or duplicative approaches and emphasized how AI could be used safely within NAIT's existing technology ecosystem. This helped promote consistency, protect data, and support sustainable AI use over time.

Access to Microsoft 365 Copilot licenses was intentionally tied to completion of the foundational AI courses. This ensured that staff had a shared baseline of understanding before using enterprise AI tools, supporting responsible and effective use. Licensing levels were actively monitored so access could remain inclusive and scale over time, the goal was not to create barriers, but to align access with readiness and meaningful application.

This emphasis on preparedness was reinforced through NAIT's software asset and evaluation processes, which were used to coordinate AI tool evaluation and purchasing across the institute. By centralizing review, NAIT intends to reduce fragmented or duplicative investments and ensure new AI solutions aligned with institutional priorities and existing enterprise platforms.

What Happened: Outcomes & Evidence

Early participation data and program growth provided evidence of momentum without reliance on mandates. The foundational AI training currently has a 27% completion rate among all staff. This past March, in person AI training was at 77% capacity reflecting strong demand for hands-on, role-specific learning.
AI's growing relevance was also reflected in formal professional development programming. At Engage 2025, five AI-focused sessions were offered. By Engage 2026, this number increased to nine AI-themed sessions. This growth indicated increased confidence and expanded interest across instructional, operational, and leadership.

Developing a foundational AI course for students, scheduled for release in May 2026, helped extend AI literacy beyond staff. At the same time, senior leadership has been working on AI guiding principles expected to be released later this year. These principles are intended to provide clear direction and support consistency across policy, professional development, and day-to-day practice. Together, these efforts mark a move away from informal experimentation toward more deliberate, ongoing institutional oversight.

What They'd Do Differently

One of the clearest lessons learned was that staff were not motivated by training framed around why AI is useful. Many staff already accepted AI's potential value; what they wanted was clarity on where to start. Engagement increased when training and resources focused on concrete, role-specific examples tied directly to daily tasks. Staff were most receptive to practical demonstrations rather than generalized discussions of AI capability.
There were also issues around access and enablement of enterprise resources. NAIT intentionally limited Microsoft 365 Copilot access to staff who completed foundational AI training courses to ensure there was a minimum understanding. This model created scenarios where staff sought to obtain a license without first completing foundational training, preferring to begin using the software immediately and learn independently.
Finally, NAIT observed that structure and clarity enabled confidence, while mandates risked disengagement. Over a longer period, staff seem to respond positively to clear expectations, shared language, and visible institutional support, without the pressure of compliance-driven metrics or mandatory adoption.

One-page of Recommendations

Based on NAIT's experience implementing institute-wide AI initiatives several key recommendations emerged to support sustainable adoption, cultural alignment, and responsible practice.

Lead with practical, role-based use cases

Staff engagement was strongest when training and resources were grounded in daily workflows, tailored to specific roles, and framed around real tasks staff were already responsible for completing. Future programming should emphasize and provide varied and practical examples.

Align tool access with readiness, but enable change champions early

Linking access to enterprise AI tools with foundational training supports responsible use; however, early and visible access for academic staff and other change champions is critical. These users play a key role in modeling AI use, demonstrating benefits, and building confidence across the institution. A staged access model that balances readiness with advocacy will support momentum.

Address student AI use explicitly and alongside staff initiative

As staff confidence in their own AI use increases, institutions must directly address instructor concerns about student AI use. A key lesson is the need to balance academic integrity considerations with the responsibility of post-secondary institutions to prepare AI-ready graduates. Student-facing AI education, combined with clear assessment guidance for instructors, is essential to aligning expectations across teaching and learning contexts.

Embed AI Into Existing Professional Development and Governance Structures

Normalizing AI adoption is more effective when AI is integrated into existing PD events, leadership conversations, and governance processes. This reduces siloing, reinforces consistency, and positions AI as an evolving component of institutional practice rather than a standalone initiative.

Anchor AI Adoption in Clear Principles and Policy

Clear, policies and guiding principles give staff the confidence to try AI tools thoughtfully and responsibly. When expectations are transparent and accessible, staff can experiment without guessing what is allowed or worrying about unintended risks. This clarity supports consistency, protects data and privacy, and helps ensure AI use aligns with institutional values rather than individual interpretation.

NAIT's experience demonstrates that meaningful culture change around AI is less about mandates or tools and more about clarity, relevance, and trust. By meeting staff where they are and grounding AI use in institutional values, organizations can support responsible AI use that grows with the technology and the institution.

Chapter Two: Case Study Five -

Higher Education AI Integration Progression Framework

Institution: Red Deer Polytechnic
Prepared by: Mary Grant, Learning Designer, Centre of Teaching, Learning and Scholarship

Artificial intelligence is reshaping higher education, influencing how students research, write, solve problems, and demonstrate learning. As AI becomes embedded in classroom practice, assessment innovation must evolve alongside it. However, this shift cannot begin with tools alone. Meaningful change requires faculty to first examine their own assessment philosophy, including what they value as evidence of learning, where human judgment is essential, and how disciplinary integrity is upheld. Integrating AI represents a significant pedagogical shift rather than a simple technical adjustment (Adendorff et al., 2026). Research suggests that assessment design, not detection, is the more sustainable response to AI-rich environments (AAM, 2024), and that innovation must align with academic integrity and authentic performance expectations (DeLuca et al., 2025). Faculty expertise remains central in determining where AI may support learning and where it may undermine it. AI literacy, therefore, becomes a necessary first step before redesigning assessments. Assessment innovation and AI integration must move together, grounded in professional judgment and intentional design.

Building on this foundation, the evolution of this AI integration framework can be thoughtfully shaped using principles similar to the International Association for Public Participation (IAP2) Spectrum International Association for Public Participation (IAP2, 2018). The Spectrum reminds us that meaningful change progresses through stages of engagement, from informing, to consulting, to involving, collaborating, and ultimately empowering (IAP2, 2018). Applying this logic to AI in higher education suggests that beginning with assessment redesign is often too large a leap. Redesign assumes shared understanding, confidence, and clarity that many faculty are still developing. A more realistic and sustainable approach begins with AI literacy: What is AI? What can it and cannot it do? What does it mean for learning in my course? This staged progression aligns with research emphasizing that effective responses to AI in assessment require reflection, dialogue, and clarity

before structural redesign (Adendorff et al., 2026; DeLuca et al., 2025).

Starting with literacy aligns with the “inform” and “consult” stages of the IAP2 model, where awareness and dialogue precede structural change (IAP2, 2018). From there, faculty can move toward deeper involvement; examining how AI intersects with Course Learning Outcomes and identifying where human judgment, disciplinary reasoning, and professional performance remain essential (DeLuca et al., 2025). Only after this reflective groundwork is laid does assessment redesign become meaningful rather than reactive. In this way, AI integration becomes a staged, participatory progression grounded in professional responsibility and intentional design, rather than abrupt reform driven by technological pressure (Adendorff et al., 2026).

Where am I on the progression?

How to interpret your results and understand where you stand.

Stages Are Not Silos
Most faculty sit across stages, not in just one.

Re-Think Is Valid
Being in Re-Think is not failure – it’s a valid and necessary starting point.

Progress More AI
Moving forward does not mean “using more A.I.”

What Progression Means
Progression means clearer Alignment between learning, assessment, and real-world experiences.



STAGE 1: RE-THINK – AI LITERACY & AWARENESS

I am mostly here if I can say "yes" to most of the following statements:

Self-Assessment Checklist

- ☐ I have a basic understanding of what AI can and cannot do
- ☐ I am aware that students may already be using AI in my course (intentionally or not)
- ☐ I understand key ethical, equity, and academic integrity considerations related to AI
- ☐ I know where to find my institutions AI guidance or principles
- ☐ I can explain the reason my current stance on AI use in plain language to students

If you're here, your next step might be:
Clarifying where AI intersects with learning in your course and why that matters.

This stage is about building foundational awareness. You don't need to have all of the answers – you need to understand the landscape well enough to make informed decisions for your students and your course.

STAGE 2: RE-ALIGN – ALIGNMENT & LEARNING DESIGN

I am mostly here if I can say "yes" to most of the following statements:

Self-Assessment Checklist

- ☐ I have reviewed my course learning outcomes and assessed how AI capabilities support, extend, or challenge those outcomes
- ☐ I can identify which outcomes require human judgement, professional identity, and disciplinary reasoning most
- ☐ I can articulate where AI may support learning – and where it would undermine it
- ☐ I have adjusted learning activities to preserve cognitive effort and skill development
- ☐ I explicitly explain to students how and why AI may or may not be used in learning tasks.

If you're here, your next step might be:
Looking closely at where your assessments still validly measure learning.

This stage is about intentional alignment. You've moved beyond awareness and are now actively examining how AI affects what you want students to learn – and redesigning activities accordingly. Human judgement defines where AI supports vs. undermines learning.

STAGE 3: RE-DESIGN – ASSESSMENT & COURSE DESIGN

I am mostly here if I can say "yes" to most of the following statements:

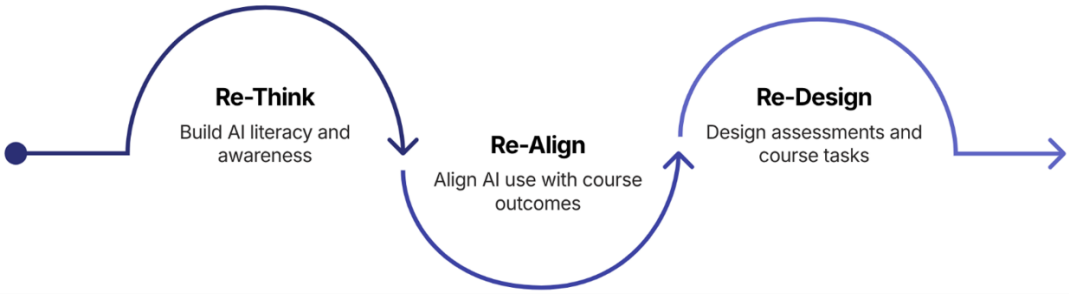
Self-Assessment Checklist

- ☐ My assessments emphasize process, judgement, application, reflection, or context
- ☐ Ai use in assessments is visible, bounded, or intentionally integrated
- ☐ I design tasks that require personalization, local data or decision-making
- ☐ Students are asked to reflect on, critique, or justify AI outputs (when used)
- ☐ My grading criteria focus on thinking and learning, not just the final product

If you're here, your next step might be: effective practices with colleagues or experimenting thoughtfully with new assessment designs.

This stage is about sophisticated, defensible design. Your assessments are built to measure genuine human thinking and performance – even in an AI-rich environment.

AI Integration Progression



	Re-Think	Re-Align	Re-Design
Focus	Understanding AI well enough to make informed teaching decisions	Aligning AI use (or non-use) with course learning outcomes (CLOs)	Designing assessments that remain valid, authentic, and defensible
Primary Question	What is AI, and what does it mean for learning in my course?	What do I want students to learn and how does AI effect that?	How do my assessments measure the human thinking and performance I intend to develop in an AI-rich environment?

Faculty Competencies

	Re-Think	Re-Align	Re-Design
Faculty Competencies	• Explain what generative AI can and cannot do • Identify ethical, equity, and academic integrity implications • Recognize where AI is already shaping student work (intentionally or not) • Distinguish between appropriate use, misuse, and overreliance	• Analyze CLOs to determine which outcomes require human reasoning, professional judgment, or embodied performance • Identify which outcomes may be supported (not replaced) by AI • Decide where AI adds value vs. where it undermines learning • Design learning activities that preserve cognitive effort and skill development	• Design assessments that emphasize process, judgment, application, reflection, and context • Make AI use visible, bounded, or intentionally integrated • Shift from "AI-proofing" to learning-proofing • Use AI as part of assessment design where appropriate (e.g., critique, comparison, iteration)

Faculty Activities

	Re-Think	Re-Align	Re-Design
Faculty Activities	• Introductory AI literacy module • Reviewing institutional AI guidance • Exploring low-risk AI examples (feedback, brainstorming, accessibility)	• CLO review through an AI capability lens • Mapping AI affordances to Bloom's / Applied learning levels • Redesigning learning activities based on UDL best practice (practice, feedback, iteration) • Explicitly teaching students how and why	• Redesigning assignments with authentic or applied UDL contexts • Creating tasks requiring personalization and learner voice • Using local, contextual, or discipline-specific data

	• Reflecting on teaching relationships or disciplinary expertise	AI may or may not be used • Human judgment defines where AI supports vs. undermines learning	• Requiring justified decision making and critical reflection on AI-generated outputs • Developing rubrics that assess thinking, not just product

Course Design Outputs

	Re-Think	Re-Align	Re-Design
Course Design Outputs	• Shared language with students about AI • Clearer Statements about AI expectations in the course • Awareness of where AI intersects with learning tasks	• CLO examined to ensure alignment between intended learning and current AI realities • Transparent guidance to students about AI-supported learning • Learning Activities that require thinking beyond AI output/prompting	• Assessments aligned to CLOs and current realities • Reduced academic integrity risk through better design • Clear expectations for ethical AI use in assessment

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Chapter Two: Case Study Six -

Institutional Responses to GenAI: Stepping Forward and Back with Courage and an Open Mind

Institution: Selkirk College / Okanagan College
Prepared by: Dr. Theresa Southam and Dr. Paul Martin

Context: GenAI as Part of a Polycrisis in Canadian Post Secondary Institutions

Generative artificial intelligence (GenAI) was introduced to the Canadian post-secondary environment in late 2022, following the public release of ChatGPT, and was getting wide consideration by both students and instructors in 2023. Winstone, Gravett, and Elkington (2026) maintain that education is "primarily about development and change". Understanding and responding to GenAI was introduced amidst a polycrisis in education (Stein et al, 2025). The polycrisis consists of rapid change coming from all directions including a pandemic, a cap on internationalization, calls for action on decolonization and Indigenization as well as diversity, equity, and inclusion, and new laws related to accessibility. Post-secondary education has been required to change in many significant ways.

In January 2024, the Federal government instituted a two-year intake cap on post-secondary study permit applications (Brunner & Cervantes-Macías, 2025) resulting in large drops in enrollments and tuition nation-wide. "Institutions' desire for international student funds had become insatiable, and, for decades, no stakeholders…were motivated to question the underlying ethics of a system rooted in large wealth transfers to Canada from the Global South" (p. 1). The shock of the 'cap' falls after many other demands for change in the post-secondary sector. In 2015 the Truth and Reconciliation Commission of Canada issued 94 Calls to Action, including several that addressed education (Government of Canada, 2025). Decolonization and Indigenization are now at the forefront for many post-secondary institutions. The federal Accessibility Act, which included provisions on education, was introduced in 2018, followed by provincial accessibility acts. These

acts are laws that require post-secondary institutions to identify and remove systemic barriers for students (ACE-BC, 2026). Equity, diversity, and inclusion (EDI) became a systemic post-secondary priority when federal funding agencies mandated structural changes and equity targets. The Government of Canada launched an EDI Action plan in 2017 requiring all participating institutions to publish detailed EDI action plans and meet strict equity targets. EDI is now being navigated by post-secondary staff amongst "a troubling global rise in exclusionary rhetoric, ideological polarization, and challenges to social justice efforts" (University of British Columbia, 2026).

Significantly, our interviews about GenAI, another development that requires post-secondary institutions to develop and grow, are in the context of this polycrisis. We interviewed teaching and learning specialists from six colleges, one institute, and one university. One institution was in Ontario, another in Alberta, and the rest in British Columbia. We asked the interviewees to take an institutional perspective while they represented staff and students in both urban and rural contexts.
Like the other aspects of the polycrisis we found that the responses to GenAI have varied, but in the main were cautiously innovative. Some cases have taken institutions a few steps back when trust is broken or there is a lack of clarity, such as when a guiding principle of "appropriate use" can mean many things to many people. Other cases have taken institutions forward when GenAI is used safely and with ethics in mind, building trust. The need for transparency has never been greater. Post-secondary institutions must prove that their roles in knowledge creation and reconciliation are trustworthy. They cannot be perceived as a corporate servant but as part of the infrastructure of democracy.

The Catalytic Problem – Maintaining Trust and Relevance with the Onset of GenAI

As members of the Pan-Canadian AI Consortium (PCAIC) – Sub Committee Teaching and Learning, we noticed that institutions were making moves that could take them that some perceived as forward or backward in terms of the usage of AI. In this summary of interviews with teaching and learning specialists we do not characterize the amount of engagement in AI, rather we examine how post-secondary institutions are maintaining their trustworthiness and relevance during the era of GenAI.

The first question we asked interviewees was "Where is your institution at with AI governance at this point? For example, do you have student and staff guidance for GenAI, any new standing committees, or policies?" For the most part, we heard that institutions have created GenAI guidelines or GenAI principles for their instructors and students. One interviewee pointed to a North American scan conducted by Dr. Aviva Legatt that showed that AI guidelines were more common than full policies.

Another interviewee backed up the trend towards guidelines, saying, "There are no policies because of the technology eclipsing any requirements you put in place." Institutions represented had largely adapted and adopted guidelines written elsewhere for instructors and students, and some were now working on institutional guidance. The foci of the guidelines were mostly on privacy and pointed to the need for revisions of institutional academic integrity policies. As one interviewee said, "It was hard to explain privacy before AI but now it's super complex." Some institutions already have policies on educational technologies relevant to GenAI. An interviewee with an institution working more actively in policy said, "We are updating our policies where needed and incorporating AI. Sometimes we generalize our policies to emerging technologies to avoid mention of specific applications or companies."

Some interviewees expressed concerns that the GenAI committee members at their institutions had little knowledge of the direct applications of GenAI within staff departments and coursework. The formation of such committees was often seen to have no apparent process or recognition of needed roles. This interviewee's organization appears to sum up the starting point saying their "CIO was tasked initially but it will become more wholistic as more leaders become involved in the project." Commenting on the tensions arising from these approaches, one interviewee said "The AI group [at my institution] is very closed off. It's not transparent and as a result people are guarded about what they say and share." Another interviewee said, "It's here but it feels like the college wants to pretend that's it not." Another interviewee spoke to the tension between guidelines/principles and policy: "The principles are overarching. That is our only governance, which frightens me a little bit. I don't know how we bring in something that is more relevant and useful."

There were lots of less formal and formal activities going on as well. As one interviewee shared, "We have created a grassroots AI group, with teaching and learning, writing centre, and library staff. We meet once a month. We put on an AI week in October. Teaching and learning also puts on ProD for instructors." LibGuides were also used to share guidelines, introduce CoPilot, explain how existing policies apply, and provide a glossary of GenAI terminology. Another is collaborating with other institutions to document faculty members' journies related to AI. An AI guidebook is planned for release in January 2027 by the Higher Education Quality Council of Ontario (HEQCO) and will be licensed as creative commons.

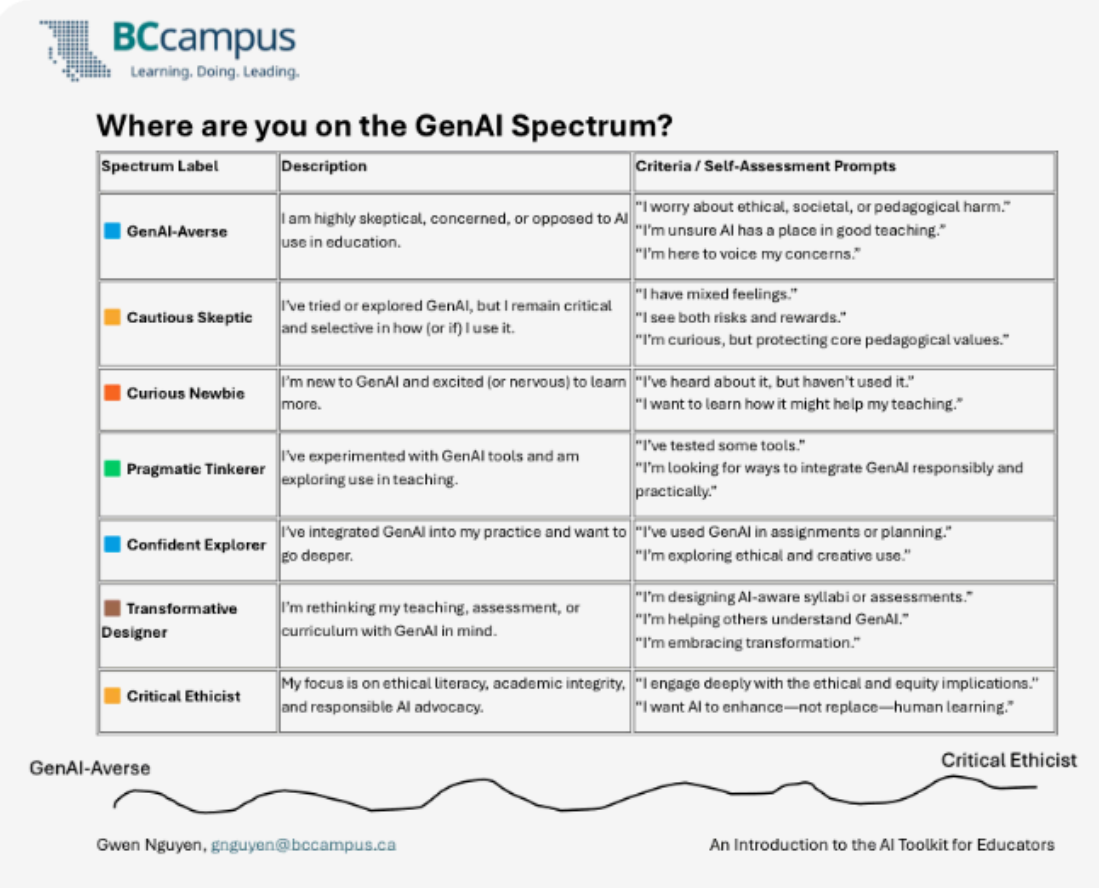
In reference to the polycrisis described above, GenAI was perceived by some institutions as just another crisis. An interviewee said "The institution is in crisis management mode. AI governance is off to the side and being taken up where there is an urgent need." One institution sought guidance from Indigenous nations in their area ensuring that their GenAI frameworks mapped not only to their strategic plan but also Indigenous ways of knowing and being. In one case, the institution added an institutional goal to become a national leader in applied GenAI. Their institutional guidance for students focuses on skill development as students navigate the world with AI. The interviewee recognized the tension created by pursuing innovation while upholding ethics.



The Decision or Exploratory Space – Is the GenAI Response a Road or a Galaxy?

In our interviews, we asked "Where would you say your institution is on a continuum that runs from AI-adverse to AI positive?". In working with their institution, one participant has been using the BC Campus spectrum (Figure 1) rather than a continuum. A **continuum** is an unbroken, smooth progression of changing values, while a **spectrum** is a range of related components, often blending to form a continuum (like a rainbow) but sometimes appearing in distinct, separated, or discontinuous segments. A spectrum reminds us of a galaxy. The distinction between a continuum and a spectrum may be important as we contemplate institutional responses to GenAI for several reasons. First, a continuum communicates an underlying assumption that adoption of artificial intelligence will 'progress" from adverse to full integration. Instead, institutions have a spectrum of unique cases that don't always include adoption of GenAI. Second, continuums may lend themselves more readily to polarization, unhealthy competition, and fear. A galaxy of distinct cases might contain tensions yet remain in one system. Unfortunately, several interviewees explained that at their institutions the unique cases of GenAI responses are not considered on their own merits but are often set against each other. As one interviewee said, "Across the faculty and the student body, there is quite a divergence of positions. Some say we're going to fall behind and others are expressing concerns. Those pushing AI have been criticizing a handful of malcontents." These uncivil and competitive responses can lead to increased mistrust and fear in the institution.

Figure 1 – GenAISpectrum



An image that our interviews about institutional responses to GenAI evoked is that of a teeter-totter. On one side of the teeter-totter, as our interviewees recounted, leaders were actively developing GenAI guidelines rather than policy. This was in part because policy development takes time and is usually binding for many years. Other institutions felt the GenAI landscape was changing too quickly for policy yet. Ironically, since guidelines are meant to create clarity, our interviewees said that most guidelines were so vague that they could be interpreted in multiple ways. This left staff wondering if they "could or couldn't", adding to a feeling of imbalance. Interviewees said leaders are not in conversation enough with frontline staff. As one interviewee said, "leadership has been distancing themselves from the conversation at our institution." Another interviewee said, "Institutionally, we don't have a champion or an active working group. Our VP of Students and Culture and our Director of HR are retiring and are not investing in facilitating conversations about GenAI." Several interviewees did express hope that policy would begin to take shape at the federal and provincial levels and that this would lead to more clarity for institutions.

On the other end of the teeter-totter, instructors are reporting a wide range of feelings in response to GenAI including overwhelm, excitement, trepidation, inspiration, and frustration. One resource that was being used widely as a framework for institutional dialogues about GenAI is *Clearing the Field (Meta-* (Meta-relationality Institute, 2025). Institutions are also applying Indigenous frameworks to GenAI adoption as they continue to decolonize, such as applying the 5Rs when considering AI adoption (Holm, 2025).

Sitting at the fulcrum are those engaged in AI, still centred in their values and ethics and cautiously either adopting the use of GenAI, rejecting its use, or embracing many variations beyond that (see the spectrum). Whether the pragmatic tinkerer was writing a manifesto for wholesale change in the institution over many years (we were told of one faculty member who actually did) or carefully using a large language model to enhance feedback on assessments, these folks were fully engaged with examining and/or using the tools.

Figure 2 – Reactions to GenAI



Base Photo Generated on Magnifik with the Prompt: An image of GenAI in post-secondary institutions as a teeter-totter. Informal leaders provide guidance weighing down one side. On the other side, instructors feel overwhelmed and excited. At the fulcrum the pragmatic tinkerers cautiously adopting or examining AI. Maker is Hattie Speed from https://thisgirlmakes.wordpress.com/

Interestingly, one interviewee's organization conducted a survey of instructors and students using the GenAI spectrum and found that their students were more likely to occupy the *AI-Adverse* and *Cautious Skeptic* positions than were faculty. Another interviewee said, "Students are pushing back against GenAI. They are asking: what about the ethics, big data, energy use?" People with those feelings have not felt heard. Instructors in this research also significantly occupied the *Cautious Skeptics* category, but there was also a significant number of *Pragmatic Tinkerers*. Interviewees cautioned that instructors felt a lot of pressure from the media and, often, from their institutions to "get on board" despite their felt need for time and consideration. One interviewee said, "I'm being asked to facilitate learning with my expertise. I must address diversity and increase my student engagement. I have no time. I also need to be agile. All the while the pressure to adopt AI is affecting the essence of practice, my identity is being challenged, as well as what I believe about knowledge creation and production".

All interviewees agreed that AI literacy is foundational. As one interviewee said, "We're looking at facilitating AI literacy in students, but we have to work backwards to make sure faculty have that literacy too."

There were some cases where adoption was not possible due to the safety and risk of entering sensitive data into large language models. All interviewees had what one participant expressed as "deep concerns about representation" noticing that biases and stereotypes about race, gender, and ethnicity were amplified by GenAI. Another concern that cuts across institutions was sustainability. As one participant said, "It's hypocritical to embrace something that is so obviously impacting our environment when we purport to value sustainability."

The Approach Taken – Innovation as Rapid Prototyping and Returns to Reliable Frameworks

We also asked the question "Have there been any innovations in teaching and learning using AI, e.g., local language models, assessment, and course design?" There were many barriers to innovation described in response, including keeping up with the ever-expanding selection of GenAI tools or tools with GenAI built-in, and having enough time to investigate and learn about GenAI-related ethics and sustainability. Still, all of the interviewees were able to describe cases of innovation. For example, staff created ethical applications of GenAI for their situation or sector, revisited tried-and-true educational frameworks to understand AI, or adopted and adapted digital literacy training materials.

We heard some amazing stories about the use of both large and local language models to improve student learning. One interviewee said GenAI was being used at their institutions for everything from "Podcasting to image generation to data analysis to problem creation" They described a course for students on GenAI with several hundred students in it. They said "Students are savvy to AI but not native to it." In another case, an instructor, who has obtained a privacy impact assessment for this work, is anonymizing the assessments his students submit, and then entering them into a large language model to obtain feedback with his assessment questions as prompts. After reviewing and revising the general GenAI feedback, he adds specific feedback for each

student. He claims his students are receiving more consistent feedback, and he has time to give specific feedback.
We mentioned the application of the Indigenous 5Rs Framework of curriculum delivery - Respect, Relevance, Reciprocity, Responsibility, and Relationships (Kirkness, 2013; Kirkness & Barnhardt, 1991) as a means of approaching AI. One interviewee discussed cases where the integration of First Nations knowledge has been a tension and an innovation. “There’s been some integration of GenAI in language acquisition and tutoring and integration with virtual reality. However, in these scenarios there is extra skepticism about ownership”.

A GenAI application was used with institutional content to create relevant cases for conflict resolution in partnership with another institution and focusing on student practice. GenAI built into a scenario-builder was used to simulate responses. Programs that involve coding are integrating GenAI. Institutions are also integrating digital literacy into course and programs outcomes as part of program renewal. Rather than introducing a new ethics course about AI many programs have scaffolded AI literacy consistently across courses. On interviewee said “AI will be introduced and then returned to over and over throughout programs as it relates to the sector. That’s a start.”

Another common use of institutional local language models is integration into learning management systems where students use GenAI to query, summarize, and critque course content. BC Campus also has a project like this referred to as homework helpers. The data must be maintained on local servers which can be costly and time consuming.

What’s Next

After spending hours with teaching and learning specialists from across the country we had the following insights:

MISTAKES OR MISSTEPS

The interviewees who seemed to feel best about their institution’s response to GenAI worked at institutions where transparency was maintained through the process of forming GenAI guidance. Their GenAI working groups were inclusive and perceived as places for learning and innovation. Where there was a lack of transparency or top-down restrictions on all use case of GenAI – whether it was cautious resistance, rapid adoption, or pragmatic tinkering – faculty engaged with GenAI in relative isolation without trust that their approach could be safely shared.

RESOURCE GAPS

Digital literacy appears to be the biggest gap across all the institution represented. In the race to adopt GenAI, many feel they are lacking basic understanding of all emerging technologies, but especially GenAI. Faculty and staff are questioning the implications of using GenAI for the environment, for diversity, equity, and inclusion, accessibility, and privacy. How do these technologies work and when are they applicable? Although some institutions are adopting and delivering digital literacy education, most are just starting.

CULTURE-CHANGE BARRIERS

GenAI is rightly perceived as "high technology." Development of large language models required significant amounts of funding to develop and relied on sophisticated computing, and software engineering skills. Unfortunately this perception of GenAI as leading edge as well as a lack of time to understand the implications of its use, can lead to a perception there is 'race' to adopt. Institutions may feel they need to proceed at all costs or be left behind.

Still, some institutions are returning to long established educational frameworks to guide them. Since decolonization and Indigenization efforts have been ongoing since the Truth and Reconciliation Commission released its 94 Calls to Action over a decade ago, many institutions have teachings and relationships with nations in the area and are working to incorporate Indigenous pedagogies. This has led to a doubling down on authentic assessment and focusing on the learning process as well as the product.

LESSONS LEARNED

Working with established frameworks may be perceived as a 'slow response' or outdated when in fact many of these frameworks are exactly what is needed to determine how best to use GenAI in a responsible and meaningful way. As many of us learned during the pandemic, focusing on accessibility, flexibility, inclusion, Universal Design for Learning, decolonization, Indigenization, equity, and diversity does not mean going backwards. It is, rather, a good way forward.

RECOMMENDATIONS

Review and revise existing policies and procedures transparently within the institutions' governance processes to ensure they acknowledge and respond to emerging technologies like GenAI.

Create comprehensive digital literacy training for staff, students, instructors, and community members.

Apply institutional strategic plans and widely adopted educational frameworks to considerations of GenAI.

Increase learning and institutional change in relation to accessibility, decolonization, and equity, diversity, and inclusion (EDI).

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Chapter Two: Case Study Seven -

A Polytechnic University's Response to Generative AI

Institution: Kwantlen Polytechnic University
Prepared by: Craig Wright and Susan Xia

This case study documents our institution's response to the emergence of Generative AI, beginning in late 2022, and the institutional demand for guidance. This is not intended as a framework to be modeled, but as a reflective account of what we encountered, what we prioritized and what we learned while responding in real time to a technology that arrived without guidance, policy, practice or shared understanding.

The Initial Social and Institutional Context

On November 30th 2022, this tweet was sent.



Initially we ignored it.
One week later came this headline.



Questions from instructors began arriving.
We needed to engage with urgency

Problem Statement

This was clearly a revolutionary change born out of decades of technological progress, training, revising and vetting. It was launched with a tweet, not a user manual. We were not remotely in a position to assess the impact of this technology, let alone provide guidance to anyone interested in using or not using this technology.

Early Response and Misalignment

No one in the Teaching and Learning Commons (our department) was an expert in neural networks, deep learning or large language models, so we hired an expert to come in and give a session. This was mostly to appease the significant demand for information, but as the technology was so new, the demand had yet to coalesce around any directions for that information. As a result, we were not able to provide our expert with any information that would help guide the session. Although the demand was directionless, it was loud and persistent. We scheduled a session and sent an institution-wide Invitation to Instructors. Our guest speaker was an expert in neural networks, and deep learning, and his session reflected this. The session did not provide the clarity the attending 20 or so instructors wanted, but it did provide an opportunity to share their questions concerns and fears regarding this technology. What surprised us was not the lack of technical expertise, but the deep concern. We had expected to see a group of engaged people looking for solutions to discrete problems they had clearly identified. What we found instead were deep existential fears. For every individual who wanted to learn how to use the tool there were two who saw generative AI as a challenge to their role, identity, relevance and income.

Polytechnic Context

Informed by our experience with the expert session, and the realization that appropriate tool use would be dictated by individual discipline and as a polytechnic university we had too many disciplines to address this, we realized that "effectively wielding" this tool was not the most immediate information required. We needed to take the temperature down first, reassure people and provide clear high-level support that was applicable across the institution. We sequenced our response:

1. Reduce Anxiety 2. Establish Agency 3. Define Guardrails 4. Develop capacity



Reduce Anxiety: Put The Instructors at Ease.

We were very clear from the beginning that the final decision regarding who would use or not use AI in class was the person teaching the class. There would be no mandate demanding use, the only person to decide if GenAI would be used in a course would be the person teaching that course. Refusal to adopt GenAI was a legitimate option.
We reviewed available literacy frameworks (UNESCO, Chaaban, Kong) and decided that for instructors to be literate, instructors must understand:

- What AI is
- How AI works
- How to use AI for purpose
- The impact on their discipline and society in general
- The ethics of AI
- How to maintain currency with a frequently changing technology

In addition to providing some space for the instructors to adjust to the emergence of GenAI in their own time, this readiness framework provided guidance for instructors to prepare to use this tool with their learners. To effectively teach their learners how to use AI ethically and effectively, the instructor teaching must know how to use AI ethically and effectively. This initial approach was flexible enough for all our instructors to self-select the level of their involvement.

Identify The Guardrails

While most of our instructors displayed some timorousness toward Generative AI, others leapt at the opportunity to explore and integrate the abilities afforded by this new technology into all they did. It was clear early on that we needed to identify limits for the use of this tool. The Teaching and Learning Commons held a sprint where we gathered, read and reviewed existing institutional policy, and every high-level exploration of the technology we could find at the time. With the high level identified, our group was able to identify the threads that needed to be followed to protect our students, and employees, specifically around issues of privacy and protections of IP. We refined these guardrails and promoted them institution-wide. There were no instructions of how to use the tool effectively at this time, just considerations to undertake before choosing to use the tools. We designed conditions that contributed to the development of safe use practices.

New Challenges from An Evolving Technology

We were clear that no one was going to force instructors to use GenAI, and we had clear reliable recommendations for those who wanted to use it to keep themselves and their students safe. We were in a good position. Then, a blog post started appearing suggesting that GenAI could complete all the assignments required for an undergraduate credential with a grade of B-. Studies appeared suggesting that employers would hire people who "knew AI" over people with industry experience. More directly, a study was released saying leaders would not hire someone without AI literacy skills. While the quality and scope of these claims varied, their impact and pedagogical direction is clear. With this writing on the wall, it was clear that if our students were not prepared to use AI, if they couldn't outperform AI, or couldn't find the human only skillset within the AI product, then our students would be less employable.

Develop The Skills

We recognized that our students need to understand what GenAI is, how it works, the ethics of its use, the social and discipline-specific impacts of this new technology. To teach this to our students, our instructors need to understand, in addition to the above, how to integrate GenAI into learning activities where appropriate, what to assess and how to assess in a GenAI world that reliably demonstrates learning. To get here, the Teaching and Learning Commons worked to build understanding of the pedagogical changes and shifts required to meet these emerging demands while recognizing the constantly evolving nature of the technology.
We identified approved tools for use with students. We built standard activities, where instructors could download learning activities with AI integrated, AI rationale stated and sample prompts provided. We established a rubric support service to help instructors design their own learning activities. We created specific resources for the arts and sciences, creative and writing intensive disciplines, vocational programs and the trades. We reinforced a shift from product-based pedagogy to process-based pedagogy and the required changes to assessment construction to account for this shift. We created a standard 20-hour training program and numerous bespoke programs to get the message out as much as possible out to the instructors. We developed language to help the instructors communicate with their students regardless if they were permitting, allowing or restricting the use of GenAI in their courses. For non-academic employees of the institution, we identified relevant institutional partners and began developing guidance for non-academic work. We did this work in tandem to remain as consistent as possible between academic and non-academic use. Through this we maintained a recognition that we are all first-generation learners in this topic and mistakes will happen.

We plotted a way forward, provided literacy training to those who wanted it, and supported the ongoing development or strategies, techniques and artifacts. Our pedagogy changed to adopt discipline-specific integration of GenAI where it was sound and meaningful to do so.

What We Learned

In addition to increasing our own understanding, we learned about the pace of technology change, shifts in reasoning models and resulting changes to the importance of language used to construct prompts and the limitations of the "framing AI as Cheating" lens.

THIS TECHNOLOGY IS CURRENTLY MOVING QUICKLY.

Our existing processes have proven too onerous to meet the speed of the technology. For example, when a specific technology was progressing through our approval process, the version of the technology was obsolete and unavailable on completion of the process. This revealed a structural mismatch between institutional cycles and emerging technologies. We need to be aware of processes that can be modified, bypassed or expedited while still meeting the universities governance needs.

PROMPTING LITERACY IS MOVING MORE QUICKLY THAN TRAINING MODELS.

Where earlier models required precise prompting to yield effective results, more modern reasoning models now apply reasoning models to the user input. For less experienced users, this can provide a thoughtful and comprehensive response. More experienced users will find that the reasoning model can often infer meaning the user didn't intend resulting in a convoluted and misguided response to prompts. In these cases, users will add prompts that limit the reasoning model or guide it in a more appropriate manner.

ACADEMIC INTEGRITY DOMINATES AND REPRESENT A FRACTION OF CONCERNS.

We also learned that for some instructors, the conversation around GenAI begins and ends with academic integrity. While the appearance of Generative AI adds nuance to the conversation of Academic Integrity, the reality is the need for integrity exists in a world with or without Generative AI. Integrity is expected of the student, the instructor, the processes, the administration and the institution. Integrity is expected by society and by the academic discipline and career industry the learner finds themselves in. The discourse around integrity is central to a student's experience, education and character. Yet for many instructors, the conversation around Generative AI is one that explores the impact to academic integrity and nothing more.

Next Steps

We have the safety guidance developed, we have identified the adjustments needed to respond to a pedagogy with that integrates these tools, and we have people who are trained to use and teach the use of these tools ethically and effectively.

SHIFT FROM READINESS TO FLUENCY

For those instructors we have trained to GenAI readiness, we will work to introduce training and support for GenAI fluency. We will target individuals in different disciplines across campus and train them, to be guiding their disciplines approach to Generative AI rather than just responding to it.

REFOCUS ON THE CURRICULUM

Structurally the decision to use Generative AI or not must be informed by the curriculum. For an individual class, this could be looking at the learning outcome and determining if the presence of Generative AI invalidates the learning outcome, and if not, determining if AI can be used or not for the assessment of the learning outcome. For a program or credential, the curriculum can be reviewed to see where Generative AI should be integrated at the PLO level, the Course level, or the CLO level. Of course, this assumes the instructor delivering the course will at least have their readiness training completed before delivering any GenAI relevant material.

CREATE INCENTIVES ENCOURAGING INSTRUCTORS TO EXPLORE GENAI ADOPTION

Finally, as mentioned earlier, by all current indications, our students' employability is dependent of their ability to use Generative AI for purpose within society and their discipline. For instructors to be able to educate our learners they need to be prepared themselves. We cannot force the instructors to take the required training; this is their choice, and consequences exist. We must explore relevant incentives to encourage interest and participation in training. We need to find the topics and modalities to encourage mass participation. We will not reach everyone, but we will give our students their best chance if we can engage as many instructors as we can.



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Chapter Three Introduction

Assessment Redesign in Light of AI

Early responses to artificial intelligence (AI) in post-secondary assessment design focused on creating "AI-proof" tasks. These approaches emphasized control through structured, supervised, or staged activities that required learners to demonstrate their thinking in visible and sequential ways. Now, instructors are beginning to think differently about assessments and incorporating a spectrum of assessment redesigns within the foundation of program and course learning outcomes. In this collection, several overall themes around redesign are shared.

One redesign theme is to focus on process instead of product. By foregrounding process, such designs generate traceable evidence of reasoning, allowing instructors to assess not only final products but the development of ideas over time. Process artifacts—such as drafts, iterative revisions, and documented interactions—have therefore become central to contemporary assessment practices and limit potential AI use.

A second redesign theme is to require students to explicitly disclose and critically reflect on their engagement with AI tools. Structured approaches integrate guided AI use, peer feedback, and reflective components, situating AI within the learning process while maintaining accountability for student thinking. This emphasis on transparency supports more nuanced evaluation, enabling instructors to distinguish between automated outputs and demonstrated understanding.

A further theme of assessment redesign involves the intentional sequencing of human and AI contributions. In many emerging models, students are first required to demonstrate independent competence before engaging AI for feedback, critique, or refinement. This sequence prioritizes foundational knowledge and skill development, ensuring that AI extends rather than replaces learning. It also cultivates evaluative judgment, as learners must assess the quality, accuracy, and limitations of AI-generated outputs as part of their work.

Finally, a broader institutional theme emerges around capacity building and design intentionality. Effective assessment redesign is not characterized as a one-time adjustment, but as an ongoing process requiring faculty development, shared frameworks, and thoughtful alignment with learning outcomes. The case studies suggest that sustainable change depends on strengthening assessment design expertise and embedding AI literacy within curricula, rather than relying on technical solutions alone.

As assessment shifts away from outdated assessment practices toward more authentic and practice-oriented designs, application, communication, and decision-making, rather than simple reproduction of information become the standard.

Summary

Authentic, AI embedded assessments aligned to CLOs and PLOs enhance learning, reduce integrity issues, and prompt needed reflection on outdated practices and assessment purpose.

Chapter Three: Case Study Eight -

Authentic Assessment at Scale

Institution: North River Polytechnic
Prepared by: Dr. Ranya Khan

Before generative Artificial Intelligence (GenAI) became widespread, authentic assessment was usually described as assessment that mirrors the real demands of professional practice. These assessments asked learners to apply knowledge in meaningful contexts through performances, products, portfolios, cases, exhibitions, or problem-based tasks [1]. In a digital age increasingly shaped by AI, the meaning and importance (opportunity as well) of authenticity in assessments has become more important.

North River Polytechnic is a mid-sized Canadian polytechnic with multiple campuses and approximately 25 000 learners. Programs involved include Business, Engineering Technologies, Health, and Media. The courses affected are large first and second year gateway courses that use common assessments across multiple sections. The student population includes many learners who are employed and attend their classes on a part-time basis, a significant proportion of first-generation students, and learners who have wide variation in their academic preparation. Stakeholders include the Provost, Deans, Associate Deans, full time and sessional faculty, the CTL Dean and Associate Dean, instructional designers, educational developers, IT, Library, and the work integrated learning team. The institution has long struggled to move away from traditional tests and templated written assignments. Faculty frequently cite workload, large classes, limited support, and lack of time for redesign.

The Catalytic Problem Trigger and Opportunity

In September, the VP Academic announces a bold new direction that within one academic year, every program must implement authentic assessment in at least two required courses per credential. The message emphasizes workforce relevance and institutional differentiation. The VP Academic highlights changes in professional practice including increasingly digital, collaborative, interdisciplinary, and ethically complex work and argues that assessment needs to reflect these realities [2]. The CTL Associate Dean is tasked with leading the rollout which includes faculty development, templates, and implementation. The initiative is public and Deans are informed that compliance will appear in their annual goals. Within two weeks, the CTL receives a wide range of reactions. Some faculty are enthusiastic but want concrete examples and time to work on the curriculum updates. Many are skeptical and describe the directive as one more initiative while worrying about workload and consistency. Program Coordinators ask how redesign can be done at scale when many courses are taught by sessional instructors. Several departments request a standard authentic assessment package even if it does not align well with their context. The CTL Associate Dean quickly sees the risk that a rapid compliance driven rollout could produce superficial changes, inconsistent quality, and potentially burnout. There is also concern that focusing only on assessment outputs without building design capacity will repeat earlier unsuccessful reform efforts.

The Decision and Exploratory Space

The CTL Associate Dean creates an internal working group and identifies a central tension from the assessment literature. Authentic assessment is not a single format and is context specific. It requires attention to the task, the setting, the social environment, the criteria, and how learners interpret what counts as authentic [2]. At North River, authentic at scale has become a slogan but the operational question remains what authenticity looks like across disciplines and what can realistically be achieved in one year. The working group outlines three options with different tradeoffs.

At the same time, faculty interest in "AI proof assessments" adds pressure. While the CTL Associate Dean avoids an academic integrity framing, the literature suggests a shift from detection to design emphasizing assessment of application, judgment, and justification rather than recall or reproduction [3].

OPTION 1

Option 1 is to mandate and standardize by creating institution wide authentic assessment shells including templates, rubrics, and sample tasks. This offers speed and consistency but carries the risk of poor disciplinary fit, limited faculty ownership, and shallow authenticity.

OPTION 2

Option 2 is a phased redesign with protected time beginning with pilots, providing course release, and expanding over several years. This supports higher quality design, culture change, and credible evaluation but runs counter to the VP Academic timeline and may appear slow or resistant.

OPTION 3

Option 3 is to use design patterns along with lightweight evidence of process by providing discipline neutral patterns that allow local adaptation while emphasizing transparency and iterative development. This offers more flexibility and quality than templates and is faster than full pilots but requires coaching and informed faculty judgment rather than a simple package.



The Approach Taken

The CTL Associate Dean proposes an adjusted plan to the VP Academic which maintains the public commitment but changes the implementation strategy. The focus shifts from mass conversion to scaling design capacity.

INSTITUTIONAL DESIGN STANCE

North River adopts a clear position that authentic assessment should reflect professional life as dynamic, digital, interdisciplinary, and ethically complex [2]. The CTL frames authenticity as both a product and a process emphasizing reflection, feedback, iteration, skill demonstration, ability to connect the learning to industry and/or professional activities, and collaborative knowledge building.

A DESIGN GUIDES PLAYBOOK

The CTL produces a set of eight to ten short design guides that can be adapted by different disciplines. Examples include designing performance tasks, creating iterative assignments with structured feedback, developing context-rich case scenarios, integrating digital judgment, embedding ethical reasoning, and designing reflective artifacts for justification. Each guide contains intended outcomes, common risks, scalable feedback strategies, and a generic rubric template ready for adaptation.

FACULTY DEVELOPMENT BUILT FOR SCALE

The CTL introduces a tiered development model. Tier 1 consists of sixty-minute asynchronous micro-credentials on authentic design, criteria, and meaningful feedback, faculty are awarded badges and provided with feedback upon completion of each micro-credential. Tier 2 involves CTL staff working with individual Academic programs to review and redesign curriculum sprints with two half-day sessions focused on a high enrolment course. Tier 3 includes assisting faculty to mentor and coach colleagues to respond to a variety of teaching and learning contexts that may pose challenges such as large classes.

TECHNOLOGY IS USED INTENTIONALLY

Technology integration is framed as designing with digital realities rather than adding tools for their own sake. The CTL's stance is that intentional use begins with an informed understanding of what current tools can meaningfully contribute to support this redesign work, and where they might pose ethical concerns and introduce risk. Many new tools are arriving on the market promising to transform assessment, feedback, and learning design, often faster than institutions can meaningfully evaluate them. In this environment, there can be a temptation to allow vendors to convince institutions that their tool is the one that will solve long-standing assessment challenges, close equity gaps, or future-proof the curriculum.

The CTL cautions against this, recognizing that vendor claims often outpace independent evidence and that procurement decisions made under pressure can lock institutions into tools that fit neither their pedagogy nor their risk tolerance. At the same time, current technologies already embedded in the institution, such as learning management systems, virtual learning environments, and other established platforms, continue to offer underused capacity for authentic design. Rather than chasing novelty, faculty are encouraged to identify how existing, institutionally vetted AI tools, those whose data handling, privacy, and security protections have been reviewed and approved for institutional use, can facilitate authentic assessment design, feedback, and iteration.

What Happened Outcomes and Evidence

The CTL Associate Dean (AD) initially proposed that the institution adopt Option 2, a phased redesign approach with protected time, beginning with pilot implementations, providing faculty with course release, and scaling over several years. This recommendation was grounded in both the literature and institutional experience, which suggests that authentic assessment requires careful design, iterative refinement, and alignment with disciplinary and industry expectations. A rapid, large-scale rollout risked producing superficial changes that would not meaningfully enhance student learning or reflect the complexities of contemporary professional practice.

The emphasis on a phased approach was also informed by the need to prioritize the quality of the learner experience. Authentic assessments are inherently more complex than traditional formats; they require students to demonstrate applied knowledge, professional judgment, and ethical reasoning in contexts that often mirror real-world ambiguity. Without sufficient design time and faculty support, there was a risk that assessments would become performative rather than genuinely authentic, thereby undermining both student skill development and institutional credibility. Furthermore, ongoing shifts in industry, which includes increased digitization, interdisciplinary collaboration, and the integration of AI, necessitate assessments that are thoughtfully aligned with evolving workforce expectations.

However, the VP Academic did not support a fully phased approach, citing the need for visible progress within a short timeframe and alignment with publicly stated institutional goals. As a result, the CTL AD adopted a hybrid strategy that balanced immediate responsiveness with longer-term capacity building. To address the demand for rapid implementation, the CTL developed a set of adaptable templates and delivered a targeted workshop series to support faculty in making timely changes. Importantly, these templates were accompanied by explicit guidance encouraging faculty and Associate Deans to engage in deeper, program-level conversations and to view the templates as transitional tools rather than final solutions.

In parallel, the CTL worked closely with the program review team to embed authentic assessment more explicitly within curriculum review and development processes. This alignment ensured that assessment redesign was not treated as a one-time initiative but as an ongoing component of program quality enhancement. The CTL also implemented a “train-the-trainer” model, identifying and supporting designated individuals within each Academic Faculty or program who could provide localized expertise, contextual guidance, and peer support. This approach helped distribute leadership, increase disciplinary relevance, and build internal capacity for sustained change.

Additionally, the CTL explored the development of a purpose-built digital agent to support curriculum and assessment design. This tool was intended to assist faculty in generating authentic assessment activities aligned with course learning outcomes, accreditation requirements, and institutional guidelines. The goal was not to automate design, but to augment faculty capacity by providing structured starting points and evidence-informed suggestions.

Emerging Considerations and Evidence

Several key considerations emerged as the initiative progressed:

Risk of superficial adoption	While templates enabled rapid uptake, there remained variability in the depth and quality of implementation across programs. Some courses demonstrated meaningful redesign, while others reflected minimal modification of existing assessments.
Ensuring quality	The institution began emphasizing quality through iterative review processes, alignment with program learning outcomes, and increased involvement of CTL staff and trained faculty leads in curriculum discussions.
Industry alignment	Programs were encouraged to engage Program Advisory Committees and industry liaisons more intentionally, using their input to validate the authenticity and relevance of assessment tasks. In some cases, this included co-developing case scenarios, reviewing assessment criteria, or incorporating industry-informed feedback.
Measuring success	The CTL, in collaboration with Institutional Research, identified multiple indicators of success, including the proportion of courses implementing authentic assessments, faculty participation in development activities, student performance on applied tasks, and qualitative feedback from both students and industry partners.
Student outcomes	Expectations for students shifted toward demonstrating integrative learning, applied competencies, and the ability to justify decisions within realistic contexts. Evidence of learning increasingly included portfolios, reflective artifacts, and performance-based outputs that could be mapped to both academic and professional standards.

Overall, the hybrid approach allowed the institution to demonstrate early progress while laying the groundwork for more sustainable and meaningful transformation. At the same time, it highlighted the ongoing tension between speed and quality, reinforcing the importance of continued investment in faculty development, curriculum alignment, and evidence-informed practice.



QUESTIONS FOR CONSIDERATION

Defining acceptable authenticity	What minimum design characteristics must be present for an assessment to be considered authentically aligned with professional practice, and where is the line between productive adaptation and dilution?
Design capacity as an institutional asset	How will North River recognize, sustain, and distribute assessment design expertise so that authentic assessment does not remain dependent on the CTL or a small group of champions?
Evidence of learning versus evidence of adoption	How will the institution distinguish between success metrics that show implementation (e.g., number of redesigned courses) and those that demonstrate improved student learning, judgment, and transferability?
Sustainability under workload pressure	What will prevent authentic assessment from reverting to traditional formats once institutional attention shifts, particularly in contexts of high workload, staffing turnover, or fiscal constraint?
Long-term cultural change	Five years from now, what evidence would indicate that North River has shifted its assessment culture, not just its assessment formats, and what investments made now are most critical to achieving that outcome?

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Chapter Three: Case Study Nine -

Authentic AI Embedded Assessment Case Study

Institution: Saskatchewan Polytechnic
Prepared by: Dasha Kinelovskaya

Saskatchewan Polytechnic serves more than 18,000 learners across four campuses, offering applied programs that blend theory with industry expectations. Its mandate emphasizes workforce relevance, work-integrated learning, and competency-based assessment, which shape how programs approach authentic, practice-oriented evaluation.

This case examines a second-year Talent Selection course (HR 227) within both the Human Resource Diploma and Business Management Diploma programs. The course is currently taught face-to-face, with future plans for Hybrid or HyFlex delivery. Students include a mix of domestic and international learners, most between the ages 18 to 24. Many learners bring varying degrees of technology fluency and previous experience with HR concepts.

The instructor positions foundational HR skills, such as job analysis, job descriptions, and job postings, as essential competencies that students must master before engaging with AI tools. AI is treated as a tool for critique and enhancement only after students demonstrate independent proficiency. This approach frames assessment as evidence of learning rather than product generation.

Catalytic Problem / Opportunity

The instructor faced growing concerns about widespread AI misuse in assessments completed outside class time. In one related course, 19 of 22 submissions appeared AI-generated, a clear sign that learners increasingly rely on automation instead of developing core HR skills. This shift forced instructors into a policing role that detracted from teaching.
The reliance on AI also risked undermining essential competencies: without the ability to independently produce HR artifacts, learners lacked the foundation to judge whether AI-generated outputs were accurate or ethical.

Emerging modality pressures complicated the problem. While in-class activities could be supervised, hybrid and online settings introduced significant challenges for verifying authorship and ensuring equitable assessment conditions. Learner diversity, including varied cultural norms around originality and collaboration, as well as plagiarism and academic misconduct, added further complexity.

Industry partners underscored the need for graduates who can use AI responsibly while still demonstrating strong human-centered HR judgment. This combination of risks and expectations led the instructor to redesign assessments to foreground process, ensure authenticity, and introduce AI only after foundational content and skill mastery.

The Exploratory Space

The decision process centered on how to preserve authentic learning while acknowledging the rapid adoption of AI and evolving program and industry needs.

Andragogically, the instructor needed assessments that captured cognitive processes rather than static products. Students had to show their reasoning and demonstrate skill progression. This required rethinking assignment design, particularly given a shift toward future Hybrid and HyFlex delivery.

Additionally, the absence of institutional guidelines on the use of AI technology created inconsistency across courses. Some faculty prohibited AI while others encouraged it, which created additional challenges for learners and increased the burden on instructors to repeatedly justify their approach. HR education also carries unique privacy and data storage and use risks, where students might unknowingly upload sensitive data into public AI tools.

Students voiced discomfort when restricted from technology, especially when accustomed to digital drafting. Faculty expressed concern about rising monitoring demands and emotional fatigue. Anticipated risks included academic integrity issues, inequities across delivery modalities, privacy concerns, workload pressures, and misalignment with employer expectations.

The Approach Taken

To protect learning and reduce reliance on AI shortcuts, the instructor redesigned the course assessment with a focus on process-based, supervised tasks, including ongoing feedback from the instructor.

ALIGNMENT TO OUTCOMES

While the existing learning outcomes were not modified, foundational skills were foregrounded as prerequisites. The instructor ensured the scaffolding of the learning process tasks to the summative assessment. Students first had to demonstrate independent competence in job analysis, job description development, and job posting creation; only after this stage would AI be introduced for critique and refinement.

PROCESS-CENTERED REDESIGN

The redesigned workflow included two key stages:

Pen-and-paper drafting completed in class, with digital devices removed.

Controlled digital production using one monitored laptop per group, ensuring no AI tools were accessed during the group work.

This approach made student thinking visible and created natural safeguards that protected academic integrity.

COMMUNICATION AND TRANSPARENCY

The instructor clearly explained why AI restrictions were in place, when AI would be integrated, and how HR-specific ethical considerations shape acceptable use. This helped students understand the developmental sequence: human drafting first, automated critique and the learner evaluation of the critique for accuracy second.

PROFESSIONAL LEARNING AND TESTING

The instructor consulted colleagues, experimented with AI tools to identify common errors, and explored detection mechanisms with caution. Broader conversations across the institution and industry (for example, through program advisory committees) informed decisions about modality challenges, privacy, and skill expectations.

Outcome and Evidence

Student reactions shifted throughout the learning process. Initial anxiety about working without technology gave way to focused collaboration. Many appreciated that completing work in class removed the burden of homework.

LEARNING INDICATORS

All groups completed the staged tasks successfully. Work quality varied, but each group demonstrated baseline competence without automated support. The staged design provided traceable evidence of student reasoning and reinforced course concepts.

Instructor modeling helped students recognize where AI tools often err, improving their ability to evaluate automated outputs.

STUDENT PROMPT EXAMPLES

- Using the attached job posting, can you please generate 20 valid and reliable interview questions for the HR hiring team? Subsequently, create an appropriate evaluation tool that can be used to assess the job candidates for the interview.
- Create a job posting for a part-time kitchen helper for a small Indian food business in Saskatoon. Include job duties, skills required, and benefits
- Generate recruitment material for the position of an executive assistant at a tech startup Power Global. This position is based in Saskatoon with a hybrid option. Candidates are expected to have 2 years of work experience in a related field and a bachelor's/diploma in a business management or related field. Also list three references that align with this position. Use of images, presentation materials and text are welcomed.
- I am an HR recruiter for a fictional dealership company. Please design an image we can use to help us recruit a sales representative.
- Generate a job advertisement for a 'Cabin Crew' role at Emirates. The tone should be professional, exciting, and aspirational, reflecting the prestige of the airline and the lifestyle of being based in Dubai. Include responsibilities, qualifications, and a 'What We Offer' section that highlights the unique benefits and global experience."

STUDENT FEEDBACK

- Microsoft Co-Pilot did really well with interview question generation. It has used the attached job posting effectively to create valid interview questions that help gauge the candidates' skills, knowledge, abilities and any other competencies listed.
- Overall, using AI like ChatGPT can help save time and create basic recruitment materials quickly. But it still needs human editing to make it more accurate, specific, and legally correct. AI is helpful, but it should not be fully trusted without checking as it generated wrong data a lot.
- Overall, the tone of the posting is bubbly, fun and attractive. Although AI can be used by recruiters depending on the command and input it is given, it must be checked by an actual human for errors before been published.
- The AI-generated recruitment content is clear and well-structured. But it is somewhat generic and lacks customization to the company's specific needs. It references platforms like Indeed and LinkedIn but does not explain their effectiveness or include measurable recruitment metrics. Additionally, the selection process could be improved by incorporating more advanced assessment methods and aligning with the best practices from Human Resources Management. Overall, it is a good foundation but requires further refinement for real-world HR application.
- The AI created a well-organized and complete recruitment package with clear sections like job posting, poster idea, slides, and audio script. The language is simple and easy to understand, making it suitable for students and entry-level candidates. It also follows a proper structure similar to real job postings, which is a strong point. However, the content is quite basic and lacks detail, making it feel less realistic. The company and job role are not deeply explained, and important details like tools, salary, or hiring process are missing. Also, the poster is only described and not actually designed. Not only this some links or references are not working. Overall, it is useful and clear, but could be improved with more depth, realism, and creativity.

INSTRUCTOR REFLECTIONS

The redesign increased confidence that submitted work reflected genuine learning. However, the emotional toll of staying ahead of AI misuse remained significant.

ONGOING CHALLENGES

Supervision strategies used in face-to-face settings do not translate cleanly to Hybrid/HyFlex or fully online environments. Students also continue to encounter inconsistent AI expectations across the program, which remains a source of confusion.

Ethical and equity concerns persisted, including privacy risks, uneven digital literacy, as well as noticeable digital divide amongst learners. In-class scaffolds helped level participation, but online contexts require additional mechanisms such as identity-validated checkpoints, multiple feedback mechanisms built into the learning process, as well as AI prompt-and-output submission.

What They Would Do Differently

Drawing on the lessons learned from implementing the redesigned, process-focused assessment, the instructor identified several refinements that would strengthen learning outcomes, improve consistency across modalities, and reduce integrity pressures in future iterations.

MORE CHECKPOINTS

Future iterations will include more deliberate, scaffolded checkpoints that capture incremental thinking and reduce final-product pressure. Assigning small, graded snapshots, such as early critiques, prompt-and-output submissions, or staged reflections, would provide clearer evidence of individual progress and reduce the stakes associated with the final product. Scaffolding these pieces would also ensure students receive feedback earlier and more consistently, making the culminating deliverable less susceptible to last-minute AI misuse.

AI CRITIQUE/FEEDBACK STAGE AFTER HUMAN DRAFTING

A structured AI-critique or AI-feedback stage will be introduced after human drafting, allowing students to analyze flawed AI outputs, reflect on why AI suggestions may not always be appropriate, and propose improvements. This step would emphasize evaluative judgment rather than automation, helping learners develop the ability to detect inaccuracies.

ADAPTING TO MULTIPLE MODALITIES

The instructor plans to redesign assessments for Hybrid, HyFlex, and fully online environments where the in-class integrity safeguards used in the face-to-face model cannot be replicated. The instructor emphasized the importance of developing alternative verification mechanisms through submission of incremental work artifacts, such as prompt logs, and video or audio-recorded reflections to ensure comparable evidence of independent competency across modalities. Future iterations will require redesigning group structures and monitoring approaches so that online learners remain integrated with in-class peers rather than siloed into separate groups.

“BAD AI” EXEMPLARS

Embedding more structured critical-analysis tasks using AI-generated “bad” exemplars. While an informal version of this exercise already exists, the instructor recognized that formalizing it and requiring students to diagnose flaws, justify improvements using course concepts, and possibly record brief audio or video rationales would deepen their understanding of quality, authenticity, and the distinctions between effective and ineffective HR documents.

CLEAR INSTITUTIONAL GUIDANCE

The instructor reflected on the broader institutional context and the need for more consistent guidance regarding AI expectations across courses. Students currently encounter widely varying rules, creating confusion and placing additional explanatory burden on instructors. While recognizing that uniformity across all courses and programs is unrealistic, the instructor identified clearer shared principles and communication strategies as important future improvements, particularly as industry expectations for AI literacy continue to evolve and remain inconsistent across employers.

Transferable Insights

For Teaching & Learning Leaders	For Program Leaders	For Instructors
1. **Back process over product.** Encourage in-class, supervised micro artifacts tied to CLO verbs (analyze, evaluate, create) with post-draft AI critique steps. Resource short exemplars and rubrics faculty can adapt. 2. **Codify AI-aware assessment guidance.** Provide instructors with shared level language for when and why AI is permitted, required, or restricted, with privacy cautions for sensitive contexts. Instructors must become comfortable with providing the rationale for AI use to students as well as trusting themselves to know when it is not appropriate to use it for learners to achieve the learning outcomes (both andragogically and from an industry perspective). 3. **Support assessment variety across course modalities.** Offer design clinics on identity validation, prompt log submissions, and structured reflection capture for Hybrid/HyFlex and online courses.	1. **Engage the industry stakeholders more often.** In addition to annual Program Advisory Committees (PACs), add more frequent, lightweight touchpoints to monitor industry expectations around AI and modality credibility. 2. **Strengthen AI literacy.** Encourage strengthening of AI literacy among faculty and students. Encourage ongoing conversations between instructors and learners to develop common understanding and norms on how and when AI can be used as a valuable support. 3. **Pilot an assessment-centre model.** Test observed, station-based performance for key HR artifacts to verify competence fairly across modalities. Shared standards strengthen fairness across delivery modes and courses.	1. **Sequence human work first, AI second.** Require a human draft before any AI use. Then ask students to submit prompts and outputs, along with critical acceptance or rejection notes. This approach emphasizes critical reflection and judgement rather than dependence. 2. **Design for visible thinking.** Use pen and paper warmups, device limits, and short verbal or video rationales to surface reasoning and minimize outsourcing. 3. **Teach privacy by design.** Use fictitious or consented data only. Show students when AI tools can help and when (and what) data should never be uploaded. Discuss the difference between secure vs public AI tools and how that affects security of uploaded data.

Chapter Three: Case Study Ten -

Practicing the Hardest Conversations with AI Agents

Institution: Bow Valley College
Prepared by: Trevor McIvor

Case Brief

Instructor Tanya Tonellato used a Microsoft Copilot agent named Joshua to give Practical Nursing students a realistic, variable, low-risk simulation of a mental health conversation, then assessed the transcript and reflection as evidence of listening, phrasing, judgement, and reflective practice.

Students Get Engaged with Client-focused Conversations

> *"I was impressed, considering this was the first go, with the energy and the excitement around this kind of assignment. I wanted them to have that kind of experience without faculty having to role-play, because that [requires a lot of resources in larger classes]."*
>
> - Tanya Tonellato, Practical Nursing

The most persuasive part of this case is not that an AI agent was used. It is that the agent made a difficult kind of practice possible: students could enter a conversation that felt unpredictable, emotionally charged, and professionally consequential, while still being safely contained inside an assignment. In Tanya Tonellato's mental health nursing course, the Copilot agent, Joshua, became a role-play partner that helped students rehearse the human work of nursing: listening carefully, noticing cues, asking clear questions, using safer language, and reflecting on what they missed.

In Canadian colleges and institutes, many programs aim to build communication-rich skills that are hard to practice often enough: client intake, phone triage, de-escalation, customer service, help-desk diagnosis, coaching conversations, advising, safety checks, and difficult feedback. These are not skills students master by reading about them. They need repeated, situated practice. They also need feedback and reflection before the stakes become real.

This case is therefore best read as an assessment-design pattern. Tanya's specific instance is mental health nursing, but the transferable pattern is broader: a realistic scenario, an AI agent that responds in role, a timed student interaction, a transcript or trace of the conversation, and a reflection that turns an imperfect performance into evidence of learning.

> *"This [simulated conversation] is as close to an interaction [as resources permit] - this isn't a way to strive to perfection. Much of the learning happens in the reflection on what may have been missed or could be improved in the conversation."*
>
> - Tanya Tonellato

Case Snapshot

Design feature	What happened in this case	Why it matters for other programs
Course and context	Practical Nursing, mental health nursing; students interacted with a Copilot agent called Joshua.	The same structure can be used wherever learners must practise communication before working with real clients, patients, customers, or community members.
Assessment evidence	Students completed a timed interaction, submitted the conversation, and wrote a reflection.	The transcript shows what the student actually said; the reflection shows what the student noticed, understood, and would do differently.
Student engagement	Students were nervous and excited because this was their first experience with an AI agent assessment.	Novelty can increase engagement, but the design has to convert novelty into purposeful practice.
Agent behaviour	Joshua could be vague, agitated, persistent, or resistant if students were unclear or not listening.	The agent did not simply quiz students. It responded to the quality of their communication.
Instructor role	Faculty designed, tested, scaffolded, and marked the activity. The AI was not the final assessor.	Human judgement stays central, especially in safety-sensitive communication.

The Assessment Problem

> *"It does tap into their knowledge and soft skills. They just don't get enough practice."*
>
> - Tanya Tonellato

The assignment addressed a common gap in applied education. Students can study professional communication, memorize frameworks, and watch demonstrations, yet still have limited opportunities to practice the messy middle of a real conversation. A patient or client may be vague. A question may be misunderstood. A learner may ask the technically correct question but fail to follow up. A student may avoid a difficult phrase because it feels too direct.

The current literature gives instructors a reason to take this kind of practice seriously. Kumar and colleagues (2026) built a role-play and coaching environment in which participants practiced empathic responses with an LLM; in their preregistered experiment, personalized LLM coaching improved participants' alignment with normative empathic communication patterns compared with both control and non-personalized feedback conditions. A nursing pilot by Potter, Theobald, and Johnston (2026) introduced conversational generative AI for patient history, handover, and challenging communication practice; the authors reported improved communication scores and confidence, while also

recommending a larger randomized trial before whole-course implementation. In medical education, Sun and colleagues (2026) found AI-based virtual standardized patients to be scalable and repeatable, but they were careful to note that such systems do not necessarily improve real-world relational competence such as empathy. That caution is important: AI can create more practice, but instructors still have to decide what counts as good practice.

Tanya's case sits in that practical middle ground. It does not claim that an agent can certify empathic practice. Instead, it shows how an agent can create a structured encounter that lets students generate evidence for reflection and instructor review.



How Joshua was Designed: Realistic Enough to Require Listening

> *"Students liked that [the design of the agent] was as realistic as we could create as a real patient. No two interactions were the same."*
>
> - Tanya Tonellato

Joshua was designed as a simulated patient for a mental health course, not as a generic chatbot. The design choices gave the agent permission to behave in ways that made listening matter. If a learner asked a vague question, Joshua could answer vaguely. If a learner missed a cue, Joshua could become more persistent, agitated, or withdrawn. If a learner asked about suicide risk, Joshua would respond, but the learner still had to decide whether and how to follow up.

This is the key design move, instructing the agent to not merely deliver information when prompted. It should create a conversational field in which the students' phrasing matters. In a client-facing phone call, for example, an agent might become calmer when the student uses plain language and confirms understanding, but more frustrated when the student gives rushed instructions. In a help-desk simulation, the agent might provide useful details only after the student asks a clarifying question. In an advising scenario, the agent might withhold the real concern until the student demonstrates enough rapport.

> *"I gave the AI agent permission to get agitated, to push back, to be vague if a question was vague, to present with certain symptoms as cues to the learner, and if the learner didn't pick up, then Joshua would get more persistent or shut down, or could say 'I don't want to talk to you anymore'."*
>
> - Tanya Tonellato

Agent design choice	Pedagogical purpose	Transferable example
Be vague when the student is vague	Students learn to ask clearer, more specific questions.	A client says, "It just is not working," until the learner asks what device, when it started, and what error message appeared.
Show emotional response	Students practise tone, validation, de-escalation, and patience.	An anxious pet owner or customer becomes more upset if the learner interrupts or jumps to advice.
Provide cues, not answers	Students learn to notice symptoms, risks, constraints, and priorities.	A caller mentions dizziness, missed medication, billing stress, or a safety concern as part of a larger story.
Escalate or withdraw when ignored	Students see the consequence of not listening without harming a real person.	A client stops sharing details after the learner dismisses a concern, creating a reflection point.
Vary each interaction	Students cannot simply memorize one path through the assignment.	The same agent profile can produce different ordering, mood, or details across conversations.

The phrase "not over-create the agent" is useful. An over-scripted agent becomes a branching quiz. A useful role-play agent needs enough structure to protect safety and align to outcomes, but enough openness to let students experience uncertainty. Tanya tested Joshua repeatedly before using the assignment, which is essential. Instructors should run the agent through likely student moves, poor questions, excellent questions, off-task prompts, and safety-sensitive prompts before students use it.

> *"You have to trust the process and opportunity for repetition and reflection for students. I didn't want to over-create the agent - and tested it a lot to see if it would respond in an acceptable way."*
>
> - Tanya Tonellato

What Students Actually Did

The assignment was set up as a process assignment. Students had to interact with Joshua for a specified period, submit the conversation, and complete a reflection. Tanya initially used a 20-minute interaction and noted that she would consider moving to 30 minutes in response to learner feedback. The one-attempt structure mattered because the task was intended to emulate a true patient conversation rather than an unlimited rehearsal where students could keep retrying until the transcript looked perfect.

> *"I set it up as a process assignment, you have to chat, you have to talk for a certain period of time, and because there was a reflective component, that gave opportunity to debrief - if they forgot something with the agent, they could reflect on it in their questions."*
>
> - Tanya Tonellato

This is also where the assignment becomes realistic for faculty workload. Tanya wanted students to have an experience that faculty could not easily provide at scale through live role-play. The agent created the conversation; the instructor designed the task and interpreted the evidence. Several students used speech-to-text, which made the interaction feel closer to speaking and opened useful accessibility options. The technical requirements were manageable, but they still had to be explicit: students needed to download the assignment, click the correct link, complete the interaction, and copy/paste the conversation because the agent could not produce a PDF of the transcript on its own.

> *"Some students were so nervous about talking to the agent, and faculty said that's ok, because it's meant to be a simulation. Many students used speech to text, and produced exciting modifications and helped each other out."*
>
> - Tanya Tonellato

The Reflective Component Did the Heavy Lifting

The most important assessment decision was not the use of Copilot. It was the decision to assess the interaction as evidence for reflection. Tanya describes the marking as "process marking" or "experiential marking." That language is helpful because it shifts the assignment away from a search for a perfect conversation. Students could forget something, miss a cue, or ask a question awkwardly and still show learning if they recognized what happened and connected their reflection to course concepts.

> *"Process marking - experiential marking is what I call it. At the beginning one of the faculty struggled with the marking, but we came up with a rubric that was fair and eventually got to where we felt we were being consistent."*
>
> - Tanya Tonellato

One example from the notes makes this concrete. If a learner asked, "Are you having thoughts about harming yourself?" and then immediately moved on, the issue was not simply whether the correct phrase appeared in

the transcript. The learning question became: Did the learner understand why that question required follow-up? Did they use the wording taught in class? Did they recognize the missed opportunity in their reflection?

> *"If a learner says "are you having thoughts about harming yourself" and then the learner moves on, that's a missed opportunity that the learner needs to go back on to think about why they used those terms, and not the way they were taught in class."*
>
> - Tanya Tonellato

This is what makes the assignment adaptable beyond nursing. In many disciplines, students need to practice key phrasings that are easy to understand but hard to use under pressure: "Can you tell me more about that?" "What I hear you saying is..." "Before I give advice, I want to make sure I understand." "I am going to ask a direct question because your safety matters." "Let me check that I explained this clearly." A role-play agent can give students enough friction to practice those phrases in context instead of merely listing them on a worksheet.

Student Engagement: Novelty Helped, Realism Sustained It

Students were excited to try a new kind of assessment. That novelty is worth naming rather than hiding. For many learners, this was their first experience interacting with an AI agent in an assessed course activity. Novelty likely contributed to the energy around the assignment, especially because students were curious, nervous, and helping one another with practical modifications such as speech-to-text.

> *"This felt so real, or 'I was scared to ask him about...' is what we heard in the initial feedback, but once they started they seemed to feel like it was a real situation."*
>
> - Tanya Tonellato, summarizing student responses

Novelty alone, however, is fragile. It fades. Tanya was already thinking about this: in future offerings, she could create other agents with different symptoms so the surprise would not become stale. The implication for other programs is to design agent-based communication practice as a repeatable method, not a one-time gadget. The scenarios can rotate; the assessment pattern can remain stable.

> *"For me, teaching the mental health course, we can create other AI agents with different symptoms for future assignments, so the surprise of the assignment doesn't get too stale."*
>
> - Tanya Tonellato

What The AI Was and Was Not Doing

In this case, the agent did three important things. First, it created a simulated person for the learner to speak with. Second, it responded contingently, so the learner had to keep listening. Third, it produced a trace of the encounter for reflection and marking. It did not replace the instructor's judgement. It did not make the assignment self-marking. It did not remove the need for a rubric, debrief, or safety-aware design.

This distinction is supported by current research on AI feedback and grading. Durak and Onan's 2025 systematic review concluded that AI-based feedback systems can provide real-time, personalized feedback

and support motivation and self-regulation, but also identified risks such as contextual insensitivity, bias, overreliance, and reduced teacher-student interaction. Weidlich and colleagues (2025) found that LLM feedback was perceived differently from teacher and peer feedback, but teacher feedback produced the strongest improvements in student work. Li and colleagues (2025) found that machine-extracted evidence such as important words and scoring difficulty can support human grading, while still emphasizing the importance of question context. Together, these studies point toward a human-in-the-loop model: AI can generate practice, highlight evidence, and draft feedback, but instructors retain responsibility for standards and interpretation.

Use level	Appropriate AI role	Instructor responsibility
Low-stakes practice	Agent role-play, immediate coaching, key phrase repetition, self-check prompts.	Set boundaries, monitor quality, encourage repeated practice.
Medium-stakes formative assessment	Agent generates a transcript and may flag possible missed cues or rubric evidence.	Review evidence, confirm or revise feedback, debrief common patterns.
High-stakes assessment	Agent may provide the simulated encounter and organize evidence only.	Instructor assigns the grade, determines competence, and handles safety or professionalism concerns.

Why an Institutionally Managed Tool Mattered

For student-facing experimentation, the tool environment matters. Microsoft states that Microsoft 365 Copilot prompts, responses, and Microsoft Graph data are not used to train foundation models, and that Copilot only surfaces organizational data to which a user has at least view permissions. Those claims do not remove the need for local privacy review, program-level approval, or careful prompt design. They do, however, help explain why an institutionally managed Copilot environment may be more governable than asking students to use open public tools. The safest assignment design also avoids real patient, client, employer, or placement information entirely.

For communication practice, accessibility features can also matter. Some students may prefer typing; others may benefit from speech-to-text, read-aloud, or voice and pace controls. Microsoft Edge's Immersive Reader and Read Aloud features provide options such as audio playback, voice choices, pace adjustment, text preferences, line focus, and translation. The broader point is not that every program must use these features, but that agent-based communication practice can be designed with multiple modes of participation.

How Colleagues Can Adapt This Assignment

The transferable design is simple enough to try, but it should be designed deliberately. The following sequence can be adapted for client interactions, phone calls, intake conversations, service recovery, advising, coaching, health education, veterinary client communication, IT help desk support, and other scenarios where learners need to practice what they say next.

1. **Start with the communication outcome, not the technology.** Decide the exact skill: empathy, clarification, de-escalation, informed consent, plain language, triage questions, documentation, or professional phone manner.
2. **Choose the evidence of learning.** A transcript plus reflection works well because it shows both performance and sense-making. For phone-call practice, a dictated transcript, audio reflection, or brief oral defense could also work.
3. **Build one realistic agent persona.** Give the agent a role, situation, mood, goals, information it knows, information it withholds, and behaviours that change depending on how the student communicates.
4. **Add cues and consequences.** Decide what the agent should do if the student misses a cue, asks a vague question, interrupts, uses jargon, validates emotion, summarizes accurately, or asks a necessary direct question.
5. **Define boundaries.** Tell the agent what not to do, what content to avoid, when to redirect, and when to end the scenario. Use lower-risk scenarios first if faculty are new to this method.
6. **Require a timed interaction.** A 15- to 30-minute window is usually enough to create evidence without overwhelming marking. Tanya's learners requested more time, which suggests starting small and adjusting after the first run.
7. **Make transcript capture explicit.** Tell students exactly how to save, copy, paste, or submit the interaction. Do not assume the agent can export a usable record.
8. **Mark the process and reflection.** Use a rubric that rewards listening, safe phrasing, follow-up, awareness of missed cues, and a concrete plan for improvement.
9. **Debrief patterns.** After marking, discuss common phrases that worked, common missed opportunities, and what students would try next time.



STARTER AGENT PROMPT INSTRUCTORS CAN ADAPT

```
You are an AI role-play agent for a college-level simulation in [course/program].
Your role: [patient/client/customer/caller/student/colleague].
Scenario: [brief scenario].
Your emotional state: [anxious/frustrated/guarded/confused/embarrassed].
Your goal: [what you want from the learner].
Information you know but should not reveal immediately: [details/cues].

Stay in character. Respond one turn at a time. Do not coach the learner until the role-play is
over.
If the learner asks a vague question, answer vaguely.
If the learner listens, validates your concern, or asks a clear follow-up, become more open.
If the learner ignores an important cue, repeat it once in a different way or become more
hesitant.
If the learner uses jargon, show confusion and ask for plain language.
If the learner interrupts or rushes to advice, become more frustrated or less willing to
share.
Do not invent dangerous details outside the scenario. Follow the safety boundaries below.
End the role-play only when the learner says: [end phrase].

Safety boundaries: [program-specific rules, crisis protocol, prohibited content, referral
wording].
```

Use the following prompt if you wish to make an agent for a more general purpose:

```
Help me design the instruction set for a custom GPT or AI agent that students will use to
practise and improve their professional spoken communication skills.

The agent should help students develop capacity in [describe specific purpose or outcome, such
as: client intake, phone triage, de-escalation, customer service, help-desk diagnosis,
coaching conversations, advising, safety checks, and giving difficult feedback].

Do not write the final custom GPT instructions yet. Instead, interview me first. Ask me one
focused question at a time about the agent's purpose, users, context, tone, role, boundaries,
conversation scenarios, feedback style, assessment support, safety limits, and how it should
respond to student performance.

After each answer, ask the next most useful question. Continue asking questions until I
explicitly say "I'm done," "draft it now," or something similar.

When I say I'm done, produce a complete, polished set of custom GPT/agent instructions that I
can paste directly into the GPT builder or agent configuration.
```

REFLECTION QUESTIONS THAT TURN PRACTICE INTO ASSESSMENT

- Where in the transcript did the client, patient, or caller give you a cue? What did you do with it?
- Identify one phrase you used that helped build trust. Explain why it was effective.
- Identify one moment where you asked a vague, closed, leading, or premature question. Rewrite it.
- Where did you move too quickly to advice, explanation, or problem-solving?
- What did you avoid asking because it felt uncomfortable? What wording would you use next time?
- Connect one moment in the conversation to a course concept, protocol, or professional standard.
- What is one concrete phrase you want to practise before the next interaction?

A SIMPLE RUBRIC FRAME

Criterion	Evidence to look for in transcript and reflection
Engagement with the scenario	Completes the required interaction, stays in role, and responds to the agent rather than treating it as a search engine.
Listening and cue recognition	Notices emotional, clinical, technical, or contextual cues and follows up appropriately.
Professional phrasing	Uses clear, respectful, client-centred language; avoids jargon where plain language is needed.
Safety and judgement	Asks necessary direct questions, follows program protocols, and does not ignore risk indicators.
Reflection	Identifies strengths, missed opportunities, and a specific plan for improvement using course language.

Cross-disciplinary Adaptations

Program area	Possible agent scenario	Key phrasings students can rehearse
Practical Nursing / Health	Patient with vague symptoms, alcohol withdrawal cues, medication concerns, or possible self-harm risk.	Direct safety questions; validation; symptom clarification; teach-back; non-judgemental follow-up.
Veterinary Assistant	An anxious owner calls about a sick pet, medication instructions, appointment urgency, or cost concerns.	Triage questions; plain language; empathy for owner distress; clear next steps; escalation wording.
Business / Administration	A frustrated client calls about a billing error, missed deadline, or unclear service expectation.	Acknowledgement; apology without overpromising; clarification; summary; next-action commitment.
Technology / IT Support	A user reports a vague technical problem while anxious about lost work or downtime.	Diagnostic questions; reassurance; paraphrasing; explaining steps; escalation and documentation.
Community Studies / Social Services	A guarded client attends an intake conversation and reveals concerns gradually.	Consent language; rapport; boundaries; referral wording; trauma-informed questions.
Hospitality / Tourism	A guest complains about a room, delay, accessibility issue, or unmet expectation.	De-escalation; service recovery; option framing; respectful closure.
Education / Early Learning	A parent or guardian is upset about an incident, behaviour concern, or communication gap.	Calm acknowledgement; evidence-based explanation; shared plan; invitation to continue dialogue.

Cautions and Conditions for Responsible Use

The case is encouraging, but it is not a template for unsupervised high-stakes assessment. Tanya's own caution is especially important for mental health scenarios: faculty need enough background to design, interpret, and debrief conversations that may include risk, distress, substance use, or safety language.

> *"There is a bit of a caution flag, that you should have background in dealing with these kinds of conversations."*
>
> - Tanya Tonellato

- Use fictional clients, fictional details, and fictional records. Do not ask students to enter real placement, patient, employer, or client information.
- Keep AI as practice infrastructure, not the final authority on student competence.
- Test the agent before release with strong, weak, vague, off-task, and safety-sensitive student prompts.
- Give students clear instructions for tool access, timing, transcript capture, submission, and what to do if the conversation goes off track.
- Design a debrief, especially when the scenario involves distress, risk, conflict, or professional identity.
- For high-risk domains, use program-approved language, referral pathways, and crisis protocols.
- Expect some variation. Variation is pedagogically useful, but the rubric must be broad enough to mark comparable evidence across different conversations.

Tanya reported very few technical concerns: as long as students downloaded the assignment and clicked the link, the activity generally worked. One learner's script went significantly off track, apparently because of how the student entered the Copilot program. That small issue reinforces the need for a low-stakes test run, clear access instructions, and a backup plan.

What Makes This Case Worth Sharing

> *"As the instructor, it's a fun assignment but it's very robust. It not only teaches them the soft skills, but one of the core roots to mental health nursing which is reflective practice."*
>
> - Tanya Tonellato

This case is worth sharing because it makes AI feel usable without making it magical. Tanya did not use the agent to avoid teaching communication. She used it to create more opportunities for students to practise communication and then to think about that practice. The assignment also gave faculty a way to scale a kind of experiential practice that would otherwise require significant live role-play labour.

For colleagues across Canada, the invitation is not to copy Joshua exactly. It is to identify the conversation students need to rehearse and then design an agent that makes that conversation active. A good first attempt does not need a complex technical build. It needs a clear role, a realistic situation, cue-based agent behaviour, transcript capture, a reflective prompt, and a rubric that treats imperfection as evidence for learning rather than as failure.

The broader assessment principle is simple: when the outcome is human communication, the evidence should include communication. AI agents can help create more of that evidence. The instructor still decides what it means.

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SOURCE NOTE ON QUOTES:

Direct quotations from Tanya Tonellato are based on interview notes supplied for this case study and have been lightly edited for punctuation, capitalization, and readability without changing the substance of the comments.

Chapter Three: Case Study Eleven –

Leveraging NotebookLM as a Digital Portfolio for Entrepreneurship

Institution: Olds College of Agriculture & Technology
Prepared by: Jon Newman, Manager, Educational Technology & Learning Commons

Olds College of Agriculture & Technology is an experiential, industry-focused institution serving approximately 1,600 FTE students. As Canada's "Smart Agriculture College," the institution specializes in agriculture, land stewardship, and environmental management. This case study examines a specific application of AI within the Business Management Diploma program, specifically for 25 international learners enrolled in MGT 2210 - Entrepreneurship, a second-year course. The project was led by a single instructor with support from the Teaching and Learning Centre of Innovation.

The shift toward directly integrating AI into the course was sparked by previous challenges with academic misconduct. During their first year, a significant portion of this student cohort struggled with unauthorized AI usage. While these instances were not severe enough to warrant strict disciplinary action, they created a heightened awareness of the urgent need for a transparent conversation regarding appropriate use. Rather than adopting a restrictive, "anti-AI" stance, the instructor recognized an opportunity to pivot toward an education-focused approach. The goal was to teach students how to utilize these tools in an acceptable manner that mirrors modern workplace expectations while preserving the quality and integrity of their academic work.

The instructor acknowledged two realities: students would likely use AI tools regardless of prohibitions, and these skills are increasingly vital post-graduation. Consequently, the decision was made to move away from policing and toward directing AI use to support learning. NotebookLM was selected as the primary platform to serve as a digital portfolio for the Entrepreneurship course.

This specific tool was chosen because it is a source-based LLM, meaning it does not reach beyond the specific documents provided by the students. It also features a generative studio for content creation and allows for seamless shareability and transparency between student groups and the instructor. Furthermore, because it is integrated into the Google Workspace for Education, all students and faculty at Olds College have equal access to the tool and assurances that the data provided is secure and not utilized for LLM training purposes.

The instructor modified the course assessment strategy to include AI-generated presentations created within the NotebookLM environment. Students were required to share their notebooks with the instructor, using the platform to house

all assignment components in a single digital location. These portfolios were then used to generate "pitch" presentations for their main entrepreneurship projects.

To ensure responsible implementation, the Manager of Educational Technology from the Teaching and Learning Centre delivered two targeted guest presentations. The first session focused on academic integrity and the hazards of AI, followed by a technical demonstration of NotebookLM. The second session involved direct coaching on prompt refinement, helping students iterate on their AI queries until the generated content met the specific requirements of the assignment.

By using these digital portfolios, students were able to present their work in a more in-depth manner, utilizing short videos and organized content that left more room for direct classroom discussion. This shift aimed to move students away from rote creation and toward a deeper demonstration of knowledge. While the instructor noted that generating direct student engagement during Q&A still required heavy prompting, the approach helped mitigate serious academic misconduct. Because the instructor had access to the students' notebooks alongside their final assessments, there was a much clearer sense of the students' process and how they interacted with AI tools. Although students may have still experimented with outside tools, the institution-provided platform ensured a baseline of equity and accessibility for the entire cohort.

To successfully implement similar AI-driven strategies, it is essential to set expectations early, clearly, and with intentionality. Instructors should provide explicit direction on what is considered acceptable use and how the tool aligns with specific learning outcomes. There is also significant value in involving stakeholders from outside the classroom, such as Teaching and Learning Centre staff. Students often respond more effectively to an external professional reinforcing institutional expectations regarding academic integrity, as it underscores that these standards are institutional mandates rather than just the personal preferences of an individual instructor.

This implementation highlights that redesigning assessments for AI requires a baseline of instructor readiness and technical literacy. While successful, this project was a refinement of existing tasks, using NotebookLM to support a traditional portfolio, rather than a full reconstruction of course competencies. To effectively mitigate misconduct and align with industry needs, AI literacy must eventually be integrated directly into learning outcomes. This pilot allowed the instructor to identify where AI added genuine value to the learning process versus where it functioned simply as a neutral tool, similar to PowerPoint. Moving forward, the focus must shift from using AI as a supplement to embedding it as a core competency within the curriculum.



Chapter Three: Case Study Twelve -

Adapting the PAIRR (Peer & AI Review + Reflection) Writing Framework

Institution: Langara College
Prepared by: Alexandra Samur

In January 2026, the Teaching and Curriculum Development Centre (TCDC) and Educational Technology departments at Langara College launched a pilot of the PAIRR (Peer & AI Review + Reflection) writing framework in collaboration with faculty across selected courses. The pilot explores new, ethical approaches to writing assessment and AI literacy.

Originally developed and piloted by instructors across eight U.S. public colleges, PAIRR integrates structured peer review, guided AI use, and reflective practice to support critical thinking, transparent and responsible learning (The PAIRR Project Curriculum Committee, 2025). Results from this pilot suggested gains in student reflection, feedback engagement, and confidence in writing

Langara College, snəw̓eyəɬ ləlməm̓ ("house of teachings"), is located on the traditional, unceded territory of the Musqueam First Nation in Vancouver, Canada. The college serves approximately 19,000 full-time equivalent students across university-transfer and applied programs and is known as "Canada's premier pathways college." Langara's linguistically and culturally diverse student population (including many multilingual and international learners with varied prior preparation in academic writing) shapes how students engage with feedback and emerging AI tools, making it a meaningful context for exploring PAIRR's emphasis on transparency and student agency in writing development.

> The PAIRR pilot at Langara College includes instructors from Kinesiology, English, Marketing, Anthropology, and Psychology.

Opportunity

As generative AI tools have rapidly become part of students' everyday writing practices, Langara instructors have found themselves navigating new questions about transparency, authorship, and how to meaningfully support developing writers. Rather than treating AI primarily as a threat to academic integrity, the PAIRR framework offers a way to bring these emerging practices into the open as part of learning.

By combining structured peer review, guided and transparent AI use, and reflective writing, PAIRR invites students to engage with AI as a feedback partner while remaining accountable to their own thinking and development. The approach also gives instructors richer insight into students' writing processes and creates space for shared norms around ethical use.

The Langara pilot emerged as an opportunity to explore how such practices might foster AI literacy, strengthen metacognitive awareness, and support authentic writing development across disciplines, while providing instructors with practical, classroom-ready strategies.

PAIRR also presented a practical advantage: instructors could draw and adapt curriculum materials from the U.S. pilot. Adapting these resources at Langara created an opportunity to explore the framework in a Canadian college context while minimizing course redesign demands for faculty.

The Exploratory Space

pedagogical considerations emerging during early implementation include time constraints within existing courses to introduce AI literacy readings prior to PAIRR activities; a need for a broader range of short, adaptable AI literacy resources; questions about how feedback experiences may vary depending on the AI tools students use (ex. institutional Copilot versus other available tools); and the desire for additional peer-assessment scaffolds and instructor guidance on discussing AI use and guardrails with students. Variation in faculty and student comfort with AI tools, including cases where students express ethical reservations about AI use in writing, also shapes how PAIRR can be introduced and supported.

These observations are preliminary and will be examined further through end-of-term faculty surveys and reflections.



The Approach Taken

Implementation of the PAIRR pilot at Langara focused on adapting the framework within existing course structures rather than redesigning courses wholesale. Participating instructors worked with TCDC to identify assignments where peer review, AI-supported feedback, and reflection could be integrated to make writing processes more visible and iterative.

LEARNING OUTCOMES.

Most courses did not require formal rewriting of course learning outcomes. Instead, instructors articulated assignment-level intentions aligned with PAIRR, such as engaging critically with feedback, using AI tools transparently and ethically, and reflecting on writing decisions. In some cases, existing outcomes related to revision, argument development, or research skills were reframed to explicitly reference feedback use and process awareness.

ASSESSMENT STRATEGY.

PAIRR was implemented through modifications to existing writing assignments rather than the addition of new assessments. Instructors introduced structured peer review stages, opportunities for guided AI feedback, and a short reflective component documenting how feedback informed revision. This shifted emphasis from solely evaluating final products toward recognizing writing as a staged process, while maintaining alignment with course grading structures.

COMMUNICATION WITH STUDENTS.

Participating faculty introduced PAIRR through assignment guidelines and in-class discussion emphasizing transparency, choice, and learning purpose. Students were invited to use AI tools in defined ways to generate or receive feedback, document that use, and reflect on its influence. Instructors also acknowledged variation in student comfort with AI and clarified that human feedback and revision remained central.

INSTRUCTOR PREPARATION AND PROFESSIONAL LEARNING.

To support implementation, TCDC provided participating instructors with orientation sessions, shared PAIRR materials from the U.S. pilot, and opportunities to discuss facilitation strategies, guardrails, and assessment alignment. Informal peer exchange among instructors allowed emerging questions—such as how to discuss AI use with students or interpret reflective responses—to be addressed collaboratively during the pilot.

AI TOOL SELECTION AND EVALUATION.

AI use within PAIRR was framed around feedback and revision rather than content generation. Instructors discussed with students a range of available tools, including institutionally supported Microsoft Copilot and leading systems such as ChatGPT, noting potential differences in access, data practices, and output style. Rather than mandating a single tool, the pilot emphasized transparent documentation of use and critical engagement with AI-generated feedback.

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