TOWARD AI-EDBOK IN INDUSTRY 4.0: QUANTIFYING AI TRANSITION READINESS AT ONTARIO'S COMMUNITY COLLEGES

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ABSTRACT

Toward AI-EdBOK in Industry 4.0: Quantifying AI Transition Readiness at Ontario's Community Colleges

This research addresses a critical gap in the standardized assessment of Artificial Intelligence (AI) readiness across Ontario's 24 publicly funded community colleges. In response to the structural challenges of Industry 4.0, it introduces a structured, reproducible framework culminating in the AI Transition Readiness Index (TRI). Unlike conventional compliance-focused tools, this model emphasizes methodological rigor, cross-institutional comparability, and policy alignment.

The methodology is organized into three tiers. The first establishes a conceptual base derived from Constructivism, Connectivism, and the author's ConnectivAI theory, which frames institutional learning as a networked, algorithmically shaped process. The second tier distinguishes between governance intent (Will) and implementation capacity (Way), operationalized through the G-PLAC framework—a calibrated realignment of the original G-PLANET-X model. The third tier integrates statistical due diligence, drawing on Lean Six Sigma practices, IMF benchmarking logic, and established principles of data validation. Leading indicators—such as AI governance structures—support predictive insight, while lagging indicators—such as program offerings and employment alignment—serve to confirm institutional outcomes.

Beyond institutional diagnostics, the study aspires to lay the foundation for an Artificial Intelligence in Education Body of Knowledge (AI-EdBOK), modeled after the Project Management Body of Knowledge (PMBOK) developed by the Project Management Institute to consolidate domain-specific expertise. AI-EdBOK is envisioned as a scalable, evolving reference to support evidence-informed governance, curriculum modernization, and sector-wide alignment in the era of intelligent systems.

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LIST OF ABBREVIATIONS

Abbreviation	Full Term
AI	Artificial Intelligence
AI-EdBOK	Artificial Intelligence in Education Body of Knowledge
AML/CFT	Anti-Money Laundering and Combating the Financing of Terrorism
ARI	AI Readiness Index (renamed to TRI)
CQAAP	College Quality Assurance Audit Process
DBA	Doctor of Business Administration
DMAIC	Define, Measure, Analyze, Improve and Control
DPMO	Defects Per Million Opportunities
FTE	Full-time equivalent
G-PLAC	Governance, Programs, Learners, Str5ategic Management Agreements, Classification of Instructional Programs
G-PLANET-X	Governance, Programs, Learners, Academic Staff, Neural networks, Employment, Technology, Experiential Learning
IMF	International Monetary Fund
IoT	Internet of Things
IRCC	Immigration, Refugees and Citizenship Canada
KCS	Knowledge-Centered Service
LMS	Learning Management System
MCU	Ministry of Colleges and Universities
NOC	National Occupational Classification
OCR	Optical character recognition
OCLS	Ontario Colleges Library Service
OECD	Organisation for Economic Co-operation and Development
OCC	Ontario Chamber of Commerce
OUCQA	Ontario Universities Council on Quality Assurance
PII	personally identifiable information

Abbreviation	Full Term
PLAC	Programs, Learners, Agreements, Classification
PLAR	Prior Learning Assessment and Recognition
PMBOK	Project Management Body of Knowledge
PMI	Project Management Institute
QA	Quality Assurance
QS	Quacquarelli Symonds
R&R	Gage Repeatability and Reproducibility
REB	Research Ethics Board
RQ	Research Question
SMA	Strategic Mandate Agreement
SSBM	Swiss School of Business and Management
TCPS	Tri-Council Policy Statement
TRI	Transition Readiness Index
UDL	Universal Design for Learning
UNESCO	United Nations Educational, Scientific and Cultural Organization
WEF	World Economic Forum

GLOSSARY OF KEY TERMS

AI Governance
The policies, structures, and oversight mechanisms by which institutions manage the risks and opportunities associated with artificial intelligence technologies.

AI Readiness
The extent to which an institution is prepared to integrate artificial intelligence into its teaching, learning, and operational practices.

Analytical AI
A branch of artificial intelligence focused on reasoning, problem-solving, prediction, and decision support through data analysis. Unlike generative AI, which produces new content, analytical AI interprets structured and unstructured data to derive insights, identify patterns, classify information, and support evidence-based conclusions. In educational and governance contexts, analytical AI is commonly used for benchmarking, diagnostics, and performance evaluation.

Chatbot
An AI-powered tool used in this study to parse and evaluate publicly available AI governance content using deterministic scoring models.

ConnectivAI
A pedagogical extension of Connectivism that incorporates AI-driven learning into the theory of distributed knowledge acquisition.

Deterministic AI
An artificial intelligence approach that produces consistent and repeatable outputs when given the same inputs, typically governed by predefined rules, fixed prompts, and constrained logic. Deterministic AI minimizes variability and reduces the likelihood of hallucinations, making it well-suited for benchmarking, evaluation, and governance applications where reproducibility and reliability are essential. See also: Hallucination.

Experiential Learning (X)
Learning through direct experience such as co-op placements, labs, or simulations. It is represented in the G-PLANET-X framework, though not fully implemented in the TRI scoring due to measurement limitations.

Generative AI
A subset of artificial intelligence focused on creating new content—such as text, images, audio, or code—by learning patterns from existing data. Generative AI models, such as large language models (LLMs), use techniques like deep learning to produce outputs that resemble human-generated content. Prominent applications include ChatGPT, DALL·E, and other tools used in education, design, and content generation.

G-PLANET-X Framework
A conceptual model for AI readiness composed of Governance (G), Programs (P), Learners (L), Agreements (A), Neural networks (N), Employment (E), Transition (T), and Experiential Learning (X).

Governance (G)
The institutional "Will" to lead and manage AI integration, measured through policy visibility, structure, and scope.

Hallucination (in AI)
A phenomenon in which an artificial intelligence system, particularly a large language model, generates outputs that are factually incorrect, fabricated, or not grounded in its training data or user input. Hallucinations can appear convincing but lack verifiable accuracy, posing risks in high-stakes applications such as academic research, governance, and education. See also Deterministic AI.

Industry 4.0
A term referring to the fourth industrial revolution, characterized by the integration of digital technologies such as artificial intelligence (AI), machine learning, robotics, the Internet of Things (IoT), and cyber-physical systems into manufacturing, education, and service sectors. Industry 4.0 emphasizes automation, data-driven decision-making, and the fusion of physical and digital systems to create smart, adaptive environments.

PLAC
The four operational “Way” dimensions of the AI Readiness Index: Programs, Learners, Agreements, and Classification.

Strategic Mandate Agreements (SMAs)
Formal agreements between Ontario’s Ministry of Colleges and Universities and each college, outlining institutional goals, priorities, and metrics.

Transition Readiness Index (TRI)
A composite, reproducible benchmarking tool designed in this study to measure Ontario colleges’ preparedness for the AI era, normalized with a baseline of 100.

CHAPTER I:
INTRODUCTION

1.1 Background and Context

The rapid acceleration of Artificial Intelligence (AI) technologies is reshaping the global economy, with postsecondary education emerging as both a participant in and a respondent to this transformation. As societies adapt to the imperatives of the Fourth Industrial Revolution (Industry 4.0), AI has evolved from a peripheral innovation to a structural force with significant implications for pedagogy, governance, and institutional strategy. Ontario's community colleges, in particular, are increasingly confronted with the dual mandate of integrating AI into instructional design and assessment practices while preserving academic integrity and upholding public accountability.

The emergence of generative large language models (LLMs), such as ChatGPT, has introduced novel and complex challenges. These include issues related to authorship, originality, and appropriate use; concerns about infrastructure and support for AI-enabled learning; and the urgent need for faculty development in digital and algorithmic pedagogies. Institutions are now under pressure to move beyond ad hoc responses and establish clear governance frameworks that can support sustainable AI adoption across academic, administrative, and operational domains.

Ontario's 24 publicly funded community colleges serve more than 188,000 full-time equivalent students (OCLS, 2024) and are positioned at the intersection of provincial workforce strategy and federal immigration policy. As such, they are expected to align educational offerings with both the Ministry of Colleges and Universities' (MCU) Strategic Mandate Agreements (SMAs) and Immigration, Refugees and Citizenship Canada's (IRCC) Post-Graduation Work Permit (PGWP) program criteria. While some colleges have responded proactively—introducing AI-specific courses or publishing AI usage guidelines—others remain in exploratory or experimental phases. In most cases, institutional approaches to AI are fragmented, lacking coherence, transparency, or measurable sustainability.

This inconsistency underscores a fundamental problem: the absence of a standardized, evidence-based framework to evaluate AI readiness at the institutional level. Without such a model, benchmarking remains arbitrary and vulnerable to the influence of anecdotal narratives. As Rauch (2021) cautions, unverified claims and institutional optimism can generate “human hallucinations,” where reputational confidence obscures the absence of actionable evidence. To counter this, the present study introduces a systematic, reproducible methodology that quantifies both strategic intent and implementation capacity across the college sector.

The focus on Ontario’s community colleges—rather than universities—is intentional. While some colleges now confer applied degrees, their institutional mandates prioritize applied learning, workforce development, and practical innovation. In contrast, universities are more oriented toward theoretical research and knowledge generation. This makes the college sector particularly relevant for assessing AI transition readiness as it relates to pedagogy, curricular alignment, and institutional responsiveness to labor market signals.

1.2 Research Problem

While jurisdictions such as the United States, Singapore, and the Netherlands have made coordinated advances in institutional AI readiness—through national strategies, investments, and policy frameworks—Ontario’s community colleges remain governed by diffuse and often inconsistent approaches. Despite their public mandate to drive workforce development in the AI era, these institutions operate within overlapping policy architectures that complicate both implementation and assessment.

At the provincial level, SMAs define key performance expectations around experiential learning, skills alignment, and graduate outcomes (MCU, 2024). At the federal level, eligibility for PGWPs increasingly hinges on alignment with the Classification of Instructional Programs (CIP) and National Occupational Classification (NOC) codes (IRCC, 2024). These layered obligations compel institutions to adapt program offerings and AI strategies in ways that are measurable, transparent, and aligned with external benchmarks.

Yet despite these imperatives, institutional responses remain uneven. A minority of colleges have adopted formal AI governance policies, introduced generative AI tools across disciplines, or developed faculty-wide professional development in AI pedagogy. Others are still navigating foundational questions regarding responsible use, technical infrastructure, and policy disclosure. The disparity reflects not only policy ambiguity but also varying degrees of operational maturity.

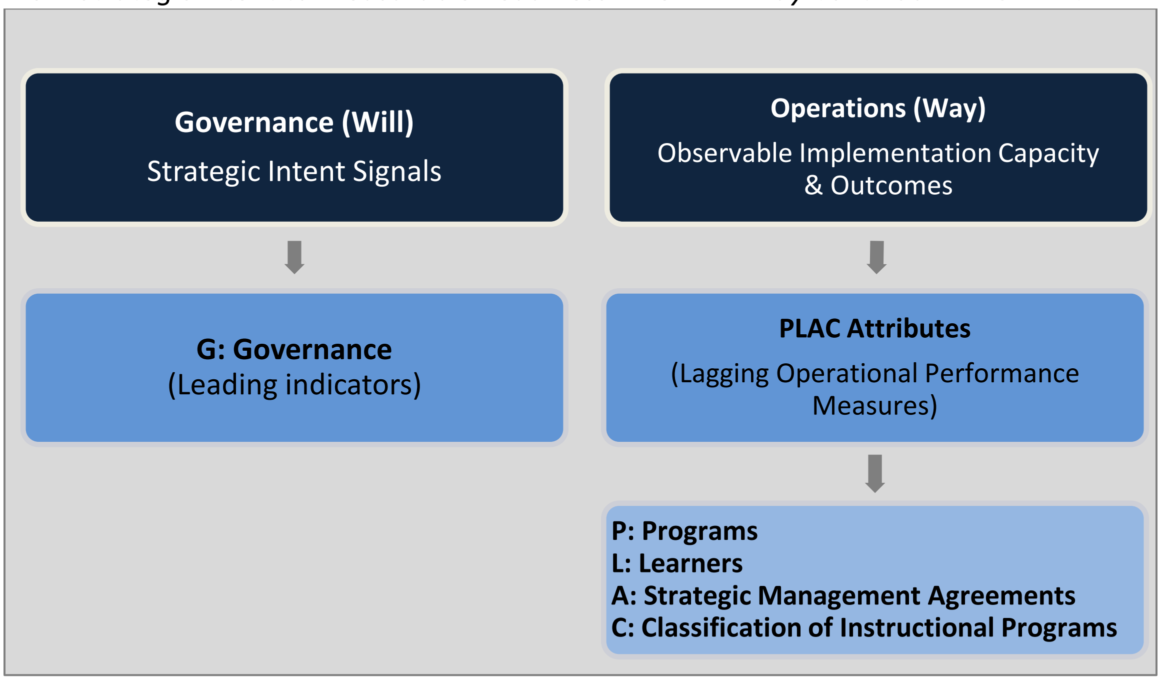
While global bodies such as the OECD (2023) and World Economic Forum (2024) have issued conceptual frameworks for AI readiness, their tools are designed primarily for national or sectoral analysis. These models lack the granularity and institutional specificity required for applied learning environments like Ontario's college system. Similarly, most existing literature on AI in education focuses on faculty attitudes, student perspectives, or individual institutional case studies—leaving a gap in reproducible, sector-wide tools that can assess both governance readiness (Will) and implementation capacity (Way).

This study responds to that gap by proposing the AI Transition Readiness Index (TRI), a reproducible framework based on the G-PLAC model. The model integrates both leading indicators—such as strategic governance intent—and lagging indicators—such as curricular delivery and labor market alignment—into a composite diagnostic tool. By grounding all measures in publicly observable, policy-relevant data, this framework provides not only a snapshot of current readiness but also a foundation for future benchmarking, planning, and investment. The diagnostic relationship between governance (Will) and implementation (Way) is illustrated in Figure 1.2, which maps the conceptual logic of the G-PLAC framework and its role in the AI readiness continuum.

This study initially employed the G-PLANET-X framework to structure the operational dimension of AI readiness, encompassing seven attributes: Programs, Learners, Academic Staff, Neural Networks, Employment Outcomes, Technology Infrastructure, and Experiential Learning. However, empirical analysis revealed that several of these dimensions—particularly Neural Networks (N) and Technology (T)—lacked standardized data sources across institutions, reducing comparability and analytic coherence. Moreover, several PLANET-X attributes overlapped significantly with one another. Faculty capacity, employment outcomes, and experiential learning participation, for instance, were already indirectly captured within program design, enrollment patterns, and policy alignment signals. To streamline and avoid double counting, the model was recalibrated into G-PLAC, which retains the underlying Will–Way logic while consolidating high-quality, policy-relevant indicators: Programs, Learners, Agreements, and Classification. This realignment harmonizes data sources, improves reproducibility, and ensures alignment with both provincial Strategic Mandate Agreements (SMAs) and federal PGWP classification policies. The result is a more parsimonious yet analytically robust framework for operationalizing institutional AI readiness.

Figure 1.2

From Strategic Intent to Measurable Readiness: The Will–Way Continuum in G-PLAC



In Figure 1.2, the Will–Way logic underpins the AI Transition Readiness Index (TRI), linking strategic governance intent (left) with operational capacity (right) through the G-PLAC framework. Governance attributes function as leading indicators of institutional AI posture, while PLAC elements serve as lagging indicators validating practical alignment with workforce, policy, and curricular objectives.

1.3 Research Purpose

The purpose of this study is to develop a scalable, reproducible framework for assessing institutional AI readiness, specifically within Ontario's 24 publicly funded community colleges. This framework responds to the lack of sector-wide benchmarks by introducing a structured model grounded in policy-relevant indicators, reproducible evaluation logic, and global comparability.

This dissertation introduces the AI Transition Readiness Index (TRI), a novel, evidence-based framework designed to evaluate institutional preparedness for AI integration across two interdependent domains: Governance ("Will") and Operational Capacity ("Way"). This dual-construct logic builds upon the Will/Way analytical model originally developed by van Eekelen (2005) and adapted here to assess organizational intent and execution in the context of systemic digital transformation.

The TRI was initially operationalized through the G-PLANET-X framework, grounded in ConnectivAI—a conceptual extension of Siemens' Connectivism, adapted for AI-augmented learning systems and institutional transitions in higher education. Governance readiness ("Will") was assessed using deterministic chatbot evaluations guided by a structured, rubric-based framework, with quality control established through Gage Repeatability and Reproducibility (Gage R&R) and Monte Carlo simulation. To ensure international comparability, the scoring framework was calibrated against the QS World's Top 10 AI Universities prior to application within the Ontario college system.

The operational dimension ("Way") was originally modeled using the seven PLANET-X attributes; however, empirical analysis revealed overlap, data inconsistency, and challenges in comparability across institutions. As a result, the model was refined into G-PLAC—a streamlined framework comprising four attributes: Programs, Learners, Agreements, and Classification. This calibrated realignment preserves the dual-construct logic while harmonizing data sources, avoiding double counting, and enhancing analytic tractability. It also aligns more directly with institutional policy obligations such as Strategic Mandate Agreements (SMAs) and federal PGWP classification rules.

To ensure methodological rigor, the "Way" component employs R-based statistical analysis of public datasets, including program offerings and enrollment trends. Conceptually, this analytic stream is informed by the International Monetary Fund's AML/CFT supervisory model, which emphasizes the use of standardized, observable indicators for institutional oversight. By relying solely on secondary data sources—such as institutional websites, government databases, and machine learning–enabled parsing tools—this study eliminates the biases often associated with interviews or self-reported surveys. The resulting methodology is fully reproducible, scalable across sectors, and purpose-built for benchmarking institutional AI readiness in policy-aligned educational systems.

1.4 Significance of the Study

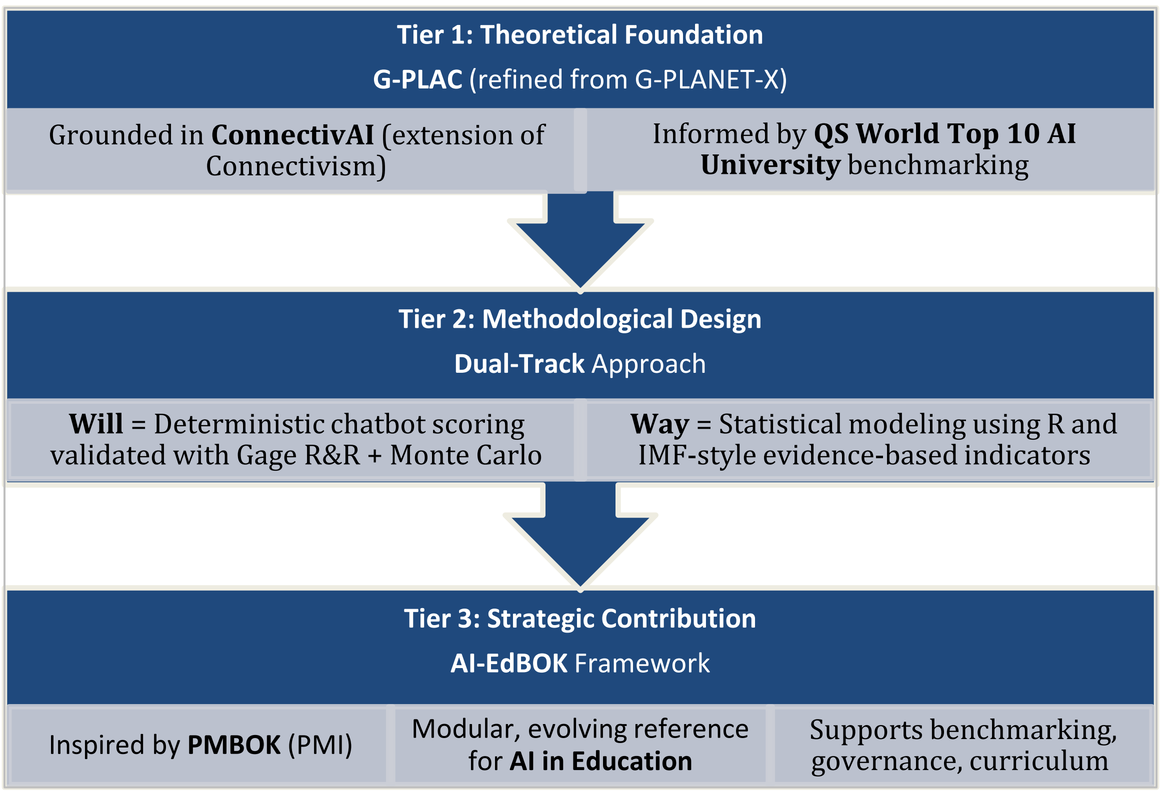
This study addresses the fragmented nature of current AI readiness assessments in the postsecondary education sector by introducing a standardized evaluation model that is both theoretically grounded and empirically reproducible. Its contributions span academic scholarship, institutional strategy, and public policy, bridging the gap between conceptual innovation and applied benchmarking in higher education.

First, the original G-PLANET-X framework—now realigned as G-PLAC—integrates core principles from educational theory, particularly ConnectivAI, a novel extension of Siemens' Connectivism adapted for AI-augmented systems. It couples this pedagogical base with comparative insights drawn from the QS World's Top 10 AI universities, providing both a theoretical and global foundation for evaluating institutional preparedness. The streamlined G-PLAC model enhances analytical clarity and avoids data redundancy by consolidating overlapping operational dimensions into four high-fidelity indicators: Programs, Learners, Agreements, and Classification.

Second, the study pioneers a dual-track methodology that combines deterministic evaluation techniques with quality assurance protocols rooted in statistical science. Governance ("Will") is assessed through rubric-based chatbot scoring, validated via Gage Repeatability and Reproducibility (Gage R&R) and Monte Carlo simulation. Where deterministic modeling is unnecessary—such as in the evaluation of curricular offerings or learner enrollment—the study applies an alternative validation logic modeled after the International Monetary Fund's (IMF) Anti-Money Laundering and Combating the Financing of Terrorism (AML/CFT) supervisory framework. This pathway emphasizes the use of standardized, observable indicators to assess institutional capacity, without introducing AI-based interpretive bias.

Third, the study lays foundational groundwork for what may evolve into an Artificial Intelligence in Education Body of Knowledge (AI-EdBOK), modeled after the Project Management Institute's PMBOK framework. AI-EdBOK is envisioned as a domain-specific, modular, and evolving knowledge architecture capable of guiding educators, researchers, and policymakers through the complex task of AI integration in teaching and learning environments. By combining reproducible metrics, policy-aligned scoring, and theoretical rigor, this framework offers a scalable approach to institutional transformation in the AI era. This three-tier structure is visually summarized in Figure 1.4.

Figure 1.4
Three-Tier Logic Underpinning the TRI Framework
(Theoretical, methodological, and strategic pillars of the TRI model—spanning G-PLAC and ConnectivAI, dual-track validation, and the long-term evolution into AI-EdBOK.)



As illustrated in Figure 1.4, the AI Transition Readiness Index (TRI) is built on a three-tier foundation: (1) a theoretically grounded G-PLAC model informed by ConnectivAI and international benchmarking; (2) a dual-track methodology integrating deterministic chatbot scoring with IMF-style statistical validation; and (3) a strategic ambition to develop AI-EdBOK—a structured, evolving knowledge architecture for guiding AI adoption in education systems.

Ultimately, this research contributes to the emerging field of AI governance in education by translating fragmented theories and disparate institutional practices into a unified, evidence-based model. It offers not only a diagnostic tool for current-state assessment but also a strategic architecture for future capacity-building in the age of autonomous and algorithmic systems.

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1.5 Research Purpose and Questions

This study investigates the extent to which Ontario's 24 publicly funded community colleges are prepared to meet the demands of the Fourth Industrial Revolution through the responsible integration of Artificial Intelligence (AI). Grounded in the G-PLAC framework—a calibrated realignment of the original G-PLANET-X model—and the Will–Way dual construct, the research assesses both strategic governance intent (Will) and measurable implementation capacity (Way).

The purpose of this research is twofold:

1. To benchmark the AI readiness of Ontario's community colleges using deterministic, reproducible tools grounded in rubric-constrained and statistically validated methods.
2. To compare these institutional results against the QS World Top 10 AI universities, identifying system-wide gaps, exemplars, and actionable insights for policy and leadership.

The study is guided by the following research questions:

- **RQ1:** To what extent do Ontario's community colleges demonstrate strategic governance ("Will") in preparing for AI integration?
- **RQ2:** To what extent do these colleges exhibit operational capacity ("Way") to deliver AI-enabled educational outcomes?
- **RQ3:** How does AI readiness in Ontario colleges compare to global best practices as observed in the QS World Top 10 AI universities?
- **RQ4:** Can a reproducible AI readiness index, grounded in rubric-constrained and data-validated methods, serve as a diagnostic benchmarking tool for policymakers and academic leaders?

To deepen this analysis, the research further articulates two sub-questions, aligning with the dual dimensions of readiness:

1.5.1 Will. To what extent do Ontario's community colleges demonstrate governance readiness through publicly accessible policies, ethical guidelines, and strategic commitments to AI adoption?
1.5.2 Way. How prepared are these institutions operationally, as evidenced by program offerings, learner participation in AI-related fields, and formal agreements aligning curricula with labor market and immigration priorities?

By evaluating both dimensions in tandem, the study offers a comprehensive, scalable model for benchmarking AI transition readiness across institutions and over time.

1.6 Structure of the Dissertation

This dissertation is organized into six chapters, each contributing to a cumulative, theory-informed, and data-driven evaluation of AI readiness in Ontario's college sector.

- **Chapter 2: Literature Review.** Surveys the foundational theories, reviews global and Canadian policy trends, and identifies knowledge gaps in institutional AI governance and operational readiness.
- **Chapter 3: Research Methodology.** Details the dual-track design of the study. The Governance dimension (Will) is evaluated using deterministic chatbot scoring, validated through Gage R&R and Monte Carlo simulation. The Operational dimension (Way)—represented by the G-PLAC model—is assessed through R-based statistical analysis and conceptually anchored in the International Monetary Fund's AML/CFT supervisory framework, which emphasizes policy alignment and observable performance indicators.
- **Chapter 4: Findings.** Presents the results of both Will and Way assessments. Governance scores reflect AI policy maturity, while normalized indicators for Programs, Learners, Agreements, and Classification are aggregated to produce the operational readiness score. These dimensions collectively generate the AI

Transition Readiness Index (TRI), a composite score supporting both provincial benchmarking and longitudinal tracking.

- **Chapter 5: Analysis and Interpretation.** Translates findings into strategic insight, addresses each research question, and proposes sectoral recommendations for improving institutional alignment with AI-era requirements.
- **Chapter 6: Conclusion and Future Directions.** Synthesizes key insights and outlines future research opportunities, including the proposed development of the Artificial Intelligence in Education Body of Knowledge (AI-EdBOK)—a modular, evolving framework designed to guide long-term strategy, governance, and pedagogy.

Figure 1.6
Dissertation Structure Mapped to the Will–Way Construct

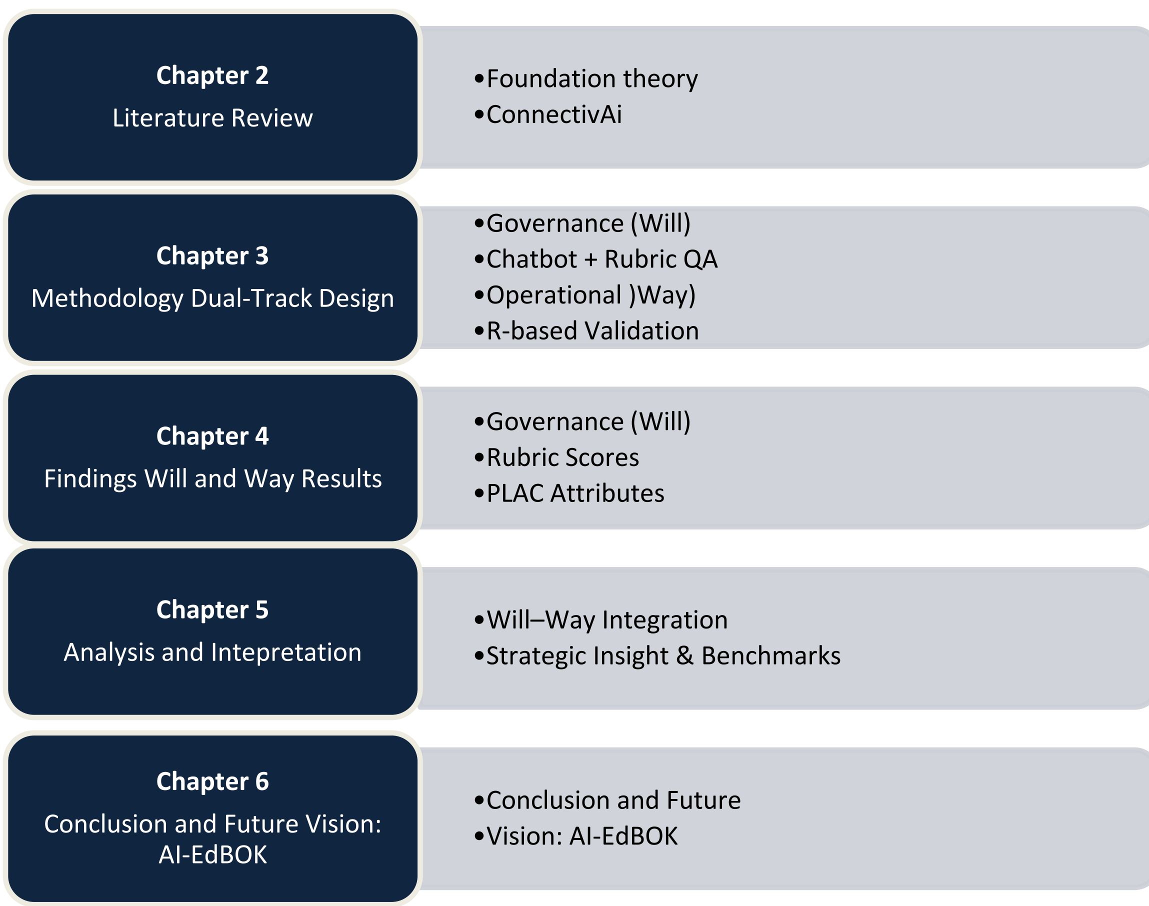

Figure 1.6 maps the structure of the dissertation to the dual-construct logic of Will and Way. Chapters 2 and 3 establish the theoretical and methodological foundation. Chapter 4 presents empirical findings on both governance intent (Will) and implementation capacity (Way). Chapter 5 integrates these results into institutional insights and Chapter 6 outlines a future roadmap through AI-EdBOK. Together, the chapters form a continuous diagnostic-to-strategy pipeline aligned with the AI readiness lifecycle.

Chapters 4 through 6 are also structured in alignment with the Knowledge-Centered Service (KCS) methodology, which emphasizes the iterative capture, refinement, and reuse of institutional knowledge (Consortium for Service Innovation, 2020). By embedding KCS logic into the dissertation's architecture, this study mirrors the dynamics of real-world knowledge ecosystems, offering not only an assessment framework but also a continuous improvement model for AI readiness in higher education.

CHAPTER II:
LITERATURE REVIEW

2.1 Theoretical Frameworks

This chapter reviews five interrelated bodies of literature that form the conceptual foundation of this study:

1. AI governance in postsecondary education.
2. Curriculum and pedagogy for the AI era.
3. Benchmarking and evaluation tools for institutional readiness.
4. Theoretical models guiding educational change in the context of AI.
5. International comparators and global benchmarking frameworks.

The synthesis of these domains reflects the strategic requirements as well as the theoretical possibilities for Ontario's community colleges as they position themselves for the challenges of Industry 4.0 and AI-driven transformation.

2.1.1 From Steam to AI: The Institutional Lag in Industrial Revolutions. Since the 18th century, humanity has experienced four major industrial revolutions, each marked by transformative technologies that reshaped economies, labour markets, and social institutions. The First Industrial Revolution, catalyzed by James Watt's steam engine, introduced mechanized production, displacing artisanal labour and prompting shifts in education and urbanization. The Second, propelled by Thomas Edison's electricity and Henry Ford's assembly line, demanded large-scale technical training and workforce specialization. The Third, or Digital Revolution, was led by pioneers such as Bill Gates and Steve Jobs, embedding computing and early automation into business and educational systems.

Today, the Fourth Industrial Revolution—or Industry 4.0—is defined by the democratization of AI, machine learning, robotics, big data, and the Internet of Things (IoT). This generation's transformative leaders are advancing technologies that not only augment productivity but also reshape the competencies required for meaningful workforce participation. As Schwab (2016) argues, the speed, scope, and systemic impact of Industry 4.0 challenge the very structures of economic and social governance.

Historically, educational institutions have often lagged behind technological shifts, adjusting curricula and governance only after workplace norms have been transformed. While each revolution was initially met with anxiety about job loss, the long-term impact has consistently proven otherwise: industries and workers retooled to produce more products and create more jobs. This historical pattern underscores the urgency of proactive institutional adaptation in the AI era.

This study positions Ontario's community colleges as institutional actors whose readiness for AI adoption must be assessed in light of this historical lag. The AI Transition Readiness Index (TRI), supported by deterministic tools and validated metrics, offers a framework to pre-emptively evaluate whether colleges are poised to meet the demands of Industry 4.0, rather than react belatedly to its consequences.

2.2 AI Governance in Postsecondary Education

AI governance in education has gained urgency as institutions grapple with the ethical, operational, and strategic implications of AI deployment. The OECD (2023) emphasizes that effective AI governance requires coherence across technology adoption, ethical safeguards, institutional transparency, and inclusivity. Despite these principles, AI governance structures in higher education—particularly in Ontario's colleges—remain underdeveloped or absent altogether.

In Canada, governance responsibilities are divided between federal and provincial governments. While Strategic Mandate Agreements (SMAs) help define college-level goals, federal initiatives like the Post-Graduation Work Permit (PGWP) shape eligibility based on labor market alignment (IRCC, 2024; MCU, 2024). However, few institutions have translated these mandates into concrete AI oversight structures, such as advisory boards or standing committees.

Robinson and Komesch (2018) argue that Canada's polytechnic institutions, including community colleges, are uniquely positioned to address national economic challenges through applied research and workforce development, such as Prior Learning Assessment and Recognition (PLAR) to smooth labor market transitions. Yet they remain undervalued in national innovation strategies. Their analysis underscores the need for stronger policy frameworks to recognize and leverage colleges' contributions to "near-to-market" innovation—particularly in the AI domain.

Global consensus is rapidly forming around the need for AI governance structures that go beyond institutional boundaries. The First International AI Safety Report (Hinton et al., 2024), commissioned by the UK government following the AI Safety Summit at Bletchley Park, synthesizes the current state of evidence on AI capabilities, risks, and mitigation strategies. Co-authored by 96 international experts—including Turing Award winner and 2024 Nobel Laureate Geoffrey Hinton—the report reflects a multi-stakeholder effort involving 30 national governments, the UN, the OECD, and the EU.

The report emphasizes that advanced AI systems pose not only technical challenges but governance and societal risks that require proactive frameworks at all levels. These findings reinforce the urgency for educational institutions—including non-research colleges—to develop transparent, ethical, and adaptive approaches to AI integration. Such imperatives validate the inclusion of AI safety and governance as foundational elements in institutional readiness models like G-PLANET-X.

2.3 Curriculum and Pedagogy for the AI Era

Integrating AI into educational systems requires more than technical adoption; it demands a fundamental pedagogical transformation. Selwyn (2019) argues that AI is not merely a tool but a powerful sociotechnical force that reconfigures how knowledge is constructed, distributed, and assessed. This transformation necessitates a critical re-examination of instructional goals, epistemic assumptions, and assessment practices.

Responding to this challenge, both national and global education authorities have called for interdisciplinary AI education that blends computational fluency with ethics, communication, and critical reasoning. The U.S. Department of Education (2022) highlights the importance of preparing learners not just to use AI, but to understand and question it. Similarly, Canada's Pan-Canadian Artificial Intelligence Strategy (ISED, 2024), launched by the federal government and managed by CIFAR, promotes AI integration through three strategic pillars:

1. Advancing AI research and talent development,
2. Developing global thought leadership on AI ethics, and

3. Supporting commercialization and adoption of AI across sectors.

Although the strategy is primarily oriented toward research and innovation, its second pillar underscores the importance of human-centric and ethically grounded AI education. The strategy implicitly calls upon educational institutions—not only research universities but also colleges—to prepare learners for participation in AI-enabled environments, both as skilled workers and informed citizens.

As part of its implementation, Canada has established three national AI institutes—Amii (Edmonton), Mila (Montreal), and the Vector Institute (Toronto)—to lead the country in AI research and talent development (CIFAR, 2024). While primarily based within research university ecosystems, these institutes increasingly recognize the essential role that community colleges play in applied learning, reskilling, and AI literacy. The common tasks that they closely work on are the training of newly emerging leaders, the startup creation, and the commercial distribution of AI innovations in various sectors. These institutes, in addition to the nationally coordinated yet locally responsive approach to AI education, also nurture the strategic imperative of aligning college-level institutions' curricula with the changing demands of the workforce and innovation ecosystems.

This pedagogical evolution is grounded in the epistemological principles of Constructivism and Connectivism (Siemens, 2005; Downes, 2008), which emphasize learning as a networked, adaptive process rather than the passive acquisition of static knowledge. Building on these frameworks, the current study proposes ConnectivAI, an AI-augmented evolution of Connectivism that conceptualizes learning as navigating, interpreting, and applying AI-mediated knowledge in real time. Rather than teaching students to master content alone, ConnectivAI encourages fluency in systems thinking, ethical reasoning, and dynamic problem-solving within algorithmically enhanced environments.

Table 2.3
Comparison of Constructivism, Connectivism, and ConnectivAI in Learning Theories

Feature	Constructivism	Connectivism	ConnectivAI*
Focus	Learner actively constructs knowledge through experience and interaction.	Learning is about connections, networks, and the ability to find information.	Learning is about navigating AI-enhanced networks, interpreting algorithmic outputs, and refining responses.
Knowledge	Knowledge is not passively received but actively built from prior knowledge.	Knowledge is distributed and external, emphasizing the ability to connect.	Situated in both human cognition and machine-generated content; includes algorithmic fluency.
Role of Teacher	Facilitator, guiding and scaffolding learning experiences.	Facilitator, supporting the creation of personal learning networks.	Orchestrator of human-AI co-learning, supporting critical engagement with AI systems.
Learning Environment	Rich, exploratory environments with opportunities for discovery.	Flexible, adaptable environments that support learner choice and connection.	Dynamic, AI-augmented spaces that require digital discernment and ethical reasoning.
Key Principles	Prior knowledge, exploration, collaboration, reflection.	Networks, self-directed learning, technology, constant change.	Human-machine interaction, prompt engineering, ethical AI use, and resilience in evolving systems.
Examples	Problem-based, inquiry-based and project-based learning.	Massive Open Online Courses (MOOCs), online communities, social media.	LLM-driven simulations, chatbot-mediated learning, adaptive assessments using AI.

*ConnectivAI is the author's original model that builds upon Connectivism to describe learning within AI-augmented knowledge ecosystems.

ConnectivAI's approach aligns with VanLeeuwen et al. (2020), who emphasize the role of instructional design support and peer networks in building institutional capacity for educational innovation. However, few models in the current literature address the specific challenges posed by generative AI, such as the integration of large language models (LLMs) into learning environments, concerns over originality and authorship, and the need for AI fluency as a digital competency.

Liberakos (2024) provides valuable qualitative data on the policy-setting experiences of senior academic leaders (SALs) in adopting technology at higher education institutions (HEIs). In an effort to embrace the Industry 4.0 wave, SALs have been concentrating on a variety of actions which include curriculum development, infrastructure renovation, partnership with industry, employee training, research initiatives and student support. The primary goal of the implementation steps is to ensure that technical institutes are in the right pace with the development of technology and to train graduates that fit the requirements of the new workforce. Additionally, prospective research could investigate whether specific, and successful, cases would demonstrate the proper achievement of these measures.

Liu's (2020) research on the universal adoption of QA frameworks in Ontario HEIs provides more information on the technical use of the measurement systems, although the outcomes were still more on the qualitative side.

Ontario's postsecondary quality assurance systems are administered through two main frameworks: the Ontario Universities Council on Quality Assurance (OUCQA) for the university sector, and the Ontario College Quality Assurance Service (OCQAS) for public colleges. Both frameworks are designed to ensure program compliance with institutional and provincial standards, focusing primarily on cyclical program reviews, credential validation, and alignment with established learning outcomes. While these systems play an important role in safeguarding educational integrity, they are not explicitly designed to assess institutional responsiveness to emerging challenges such as AI integration, digital innovation, or Industry 4.0 readiness. Both the OUCQA and OCQAS frameworks remain compliance-focused.

Jarrell and Kirby (2024) noted that quality managers at Ontario colleges play a critical role in fostering a culture of improvement, yet the frameworks themselves lack a sufficient emphasis on driving innovation or addressing Industry 4.0 requirements. The existing literature also fails to provide actionable frameworks or tools that institutions can use to assess their preparedness for Industry 4.0 systematically.

Industry feedback provides another perspective on the preparedness of Ontario's community colleges. Despite Ontario's $1.08 billion in AI-related R&D funding and the founding of 27 AI companies in 2022-23 (Veil, 2023), businesses report limited adoption of AI technologies, with only 4% of Canadian firms integrating AI into their operations (OCC, 2024). A 2024 Q3 survey finds 22% of Ontario industries cited barriers such as a lack of knowledge about AI capabilities, immaturity of AI technology, and shortage of skilled workers as reasons for not planning AI adoption in the next 12 months (Statistics Canada, 2024a). The curriculum of the colleges should be in line with the requirements of the businesses to address these disparities in the most effective manner.

In this respect, the curriculum full of transformation in the area of AI should be systemic, inter-curricular, and ethical first, training students not only to be part of the AI-run workplaces, but also to think critically about the technologies they are using and developing.

2.4 Benchmarking and Evaluation Gaps

Despite growing attention to AI readiness, most existing assessment frameworks fall short of capturing the operational realities of Ontario's community colleges. International models—such as those developed by the OECD (2023) and World Economic Forum (WEF, 2024)—tend to focus on macro-level policy or research-intensive institutions, with limited applicability to colleges whose missions are rooted in applied learning, workforce development, and community responsiveness.

While Nafea and Toplu (2021) offer valuable institutional insight through their case study on Seneca College, the narrow sample size of 112 participants limits the generalizability of their findings. In a similar vein, Liu (2020) remarks on the incompleteness of the Ontario quality assurance mechanisms for inadequacies to direct continuous improvement and observes that existing structures are much more on procedural compliance rather than innovation or responsiveness. Despite this, such frameworks cannot be used as benchmarking tools to measure the readiness of AI implementation in an identical, system-wide manner.

To fill this methodological void, this study introduces the Transition Readiness Index (TRI), a composite evaluation model that combines open-source data analytics with rubric-based scoring across eight domains. TRI advances institutional self-assessment by offering a transparent and reproducible means for benchmarking AI governance, capacity, and alignment with labor market needs.

Recent industry data further reinforces the need for such evaluative tools. Despite Ontario's investment of $1.08 billion in AI-related research and the founding of 27 AI firms in 2022–2023 (Veil, 2023), only 4% of Canadian businesses report having integrated AI into their operations (OCC, 2024). Statistics Canada (2024) in its third quarter survey for 2024 discovered that 22% of the employers from Ontario were of the opinion that AI illiteracy, technological immaturity, and workforce shortages are significant barriers to adoption. The findings expound the need for colleges to take the urgent step of evaluating their readiness, finding out gaps in their offering, and syncing their curricula with the fast-moving market demands.

2.5 From Aspirational Models to Diagnostic Frameworks

Much of the existing literature on Artificial Intelligence (AI) in education adopts an aspirational or visionary tone. These contributions often emphasize the transformative potential of AI but lack the methodological specificity required for institutional implementation. For example, van Eekelen (2022) offers a reflective framework that explores how higher education might evolve through AI integration. While such models are valuable for conceptual exploration and raising awareness, they fall short in providing measurable indicators or reproducible evaluation.

This study advances the conversation by proposing G-PLAC, a diagnostic framework that bridges educational theory, governance analysis, and structured evaluation. Unlike strategic or philosophical models that remain abstract, G-PLAC operationalizes AI readiness through a dual-construct methodology: governance intent (Will) and implementation capacity (Way). These dimensions are scored using deterministic language models and statistical tools, producing actionable outputs grounded in publicly observable, policy-relevant data.

This diagnostic orientation enables the construction of the AI Transition Readiness Index (TRI), a composite score that allows institutions to benchmark their progress against both provincial and international comparators. TRI's structure offers not only a current-state snapshot but also a mechanism for longitudinal tracking and continuous improvement. In this way, the framework advances a more rigorous, accountable, and evidence-based approach to institutional readiness in the AI era.

2.6 Global Benchmarking and Comparators

AI readiness is not merely a provincial or national concern; it is a global imperative. Postsecondary institutions across the world are responding to the rise of artificial intelligence by investing in AI-focused research, establishing ethics and governance committees, and embedding AI literacy across disciplines. Among them, a subset of elite institutions—such as those ranked among the QS Top 10 for Artificial Intelligence Research—have emerged as global leaders in shaping the pedagogical, infrastructural, and strategic foundations of AI integration. These institutions serve as valuable comparators for Ontario's community colleges, offering aspirational yet evidence-based benchmarks for what institutional AI readiness can look like in practice.

International entities have crafted an impressive range of advanced checklists to evaluate the degree of AI development at the national or complete system levels. To illustrate, the OECD AI Policy Observatory (OECD, 2023) provides region-specific indicators on AI strategies, data governance, and skills development. In a similar manner, the World Economic Forum's Global AI Readiness Index (WEF, 2024) judges national preparedness based on governance, infrastructure, and innovation metrics. UNESCO's 2022 Recommendation on the Ethics of Artificial Intelligence adds a normative layer, emphasizing equity, inclusivity, and cultural preservation in AI adoption across educational and social systems.

However, these models—while valuable—are oriented toward national governments or macro-level policy environments. They rarely offer tools that can be applied at the institutional level, and they seldom account for the operational realities of non-university institutions such as polytechnics and community colleges. Moreover, they lack reproducibility across diverse institutional contexts and fail to provide disaggregated data or metrics suitable for cross-institutional benchmarking.

To address these limitations, this study introduces a structured comparative component: the benchmarking of Ontario's 24 public community colleges against the QS World Top 10 AI Universities. These global exemplars were selected based on their consistent leadership in AI-related research output, funding, faculty expertise, and integration of AI into teaching and learning strategies (QS, 2024). Institutions such as Harvard, MIT, Carnegie Mellon, and the University of Toronto exemplify best practices in AI governance, curriculum reform, interdisciplinary collaboration, and student engagement with emerging technologies.

The Governance (G) sub-index proposed in this study will be used to evaluate and compare AI policies across both local (Ontario colleges) and global (QS Top 10) institutions. The composite AI Transition Readiness (TRI) index, which builds on the G sub-index, provides a normalized score with a baseline of 100, enabling straightforward benchmarking and diagnostic insight into institutional positioning. With the addition of this international comparison, the study further solidifies the TRI's role as a diagnostic tool and, in the process, places Ontario's college system in a more extensive global arena of preparedness for artificial intelligence. This comparative view not only improves the general folk's acceptance of the findings but also adds to the policy learning across jurisdictions.

2.7 Literature Review Summary

This chapter has reviewed the foundational literature underpinning this study across five interrelated domains.

Section 2.2 explored the growing urgency of AI governance in postsecondary education, emphasizing the lack of formal oversight structures in Ontario's colleges and aligning institutional needs with global safety frameworks such as the First International AI Safety Report (Hinton et al., 2024).

Section 2.3 examined pedagogical models for AI integration, tracing a theoretical arc from Constructivism to Connectivism and introducing the author's original

ConnectivAI model to capture the nuances of AI-augmented learning. It also demonstrated how institutional transformation requires not only curricular innovation but also faculty development and ethical discernment.

Section 2.4 addressed the limitations of current benchmarking and quality assurance frameworks, identifying the absence of reproducible, college-specific evaluation tools for AI readiness.

Section 2.5 built upon this critique by proposing the G-PLAC framework, which moves beyond aspirational models to offer a diagnostic structure that supports consistent, transparent, and policy-aligned institutional assessment.

Section 2.6 examined global benchmarking approaches, including frameworks developed by the OECD, WEF, and leading AI universities. This review provides the foundation for the cross-institutional benchmarking component of this study, which compares Ontario's colleges to the world's Top 10 AI universities using a normalized Transition Readiness Index.

While the reviewed literature provides valuable theoretical and case-based insights, it reveals a critical gap in scalable, empirical tools for measuring institutional AI readiness—particularly at the college level. Most existing studies rely on qualitative methods or narrative policy analysis, offering limited cross-institutional comparability and minimal replicability. This methodological shortfall underscores the need for a robust, quantitative model capable of supporting longitudinal benchmarking and guiding institutional strategy. This study addresses that gap through the development and validation of the Transition Readiness Index (TRI) and its underlying G-PLAC framework—offering a novel contribution to both AI education scholarship and applied institutional practice.

All these observations emphatically state the importance of a multi-dimensional, evidence-based assessment of the AI state in institutions, which not only recognizes the mission of Ontario's community colleges but also the global responsibility of AI governance. The following chapter details the steps followed in putting this operational framework into practice and verifying its reproducibility and usefulness in the institution.

CHAPTER III:
RESEARCH METHODOLOGY

3.1 Overview of the Research Problem

The accelerated advancement of artificial intelligence (AI) technologies has intensified the need for educational systems to equip learners with new competencies aligned to the demands of Industry 4.0. While universities globally have begun to integrate AI policy, research, and strategic planning into their institutional frameworks, Ontario's publicly funded community colleges face a distinct challenge: how to reconcile their workforce development mandate with the systemic and responsible adoption of AI in teaching, governance, and operations.

Ontario's 24 public colleges serve a diverse, career-oriented student population and are mandated to deliver practical, employment-focused programming. Yet, no standardized mechanism currently exists to assess their readiness for AI integration. Although international frameworks—such as those proposed by the OECD and the World Economic Forum—offer conceptual models for AI transformation, these tools are generally designed for universities or national-level systems, and lack the granularity required to evaluate applied learning institutions operating under provincial mandates.

The core research problem thus centers on the absence of an actionable, evidence-based framework that Ontario's colleges can use to benchmark institutional AI readiness in a reproducible and policy-relevant manner. Existing discourse tends to focus either on abstract governance aspirations or on technical implementation gaps, without offering a replicable mechanism for institutional self-assessment or system-wide comparison. Consequently, college leaders lack a structured roadmap for integrating AI in a way that is measurable, transparent, and aligned with public expectations and labor market needs.

To address this gap, the present study proposes a structured, dual-construct framework—G-PLAC—which evaluates institutional AI readiness through two interdependent dimensions: strategic governance intent (Will) and operational implementation capacity (Way). Grounded in ConnectivAI, the G-PLAC model incorporates educational theory, policy analytics, and reproducible data science methodologies to generate the AI Transition Readiness Index (TRI). The TRI enables colleges to assess their own progress, benchmark against peers and international exemplars, and identify evidence-based pathways for improvement.

In doing so, this study offers a theory-informed, sector-specific, and methodologically rigorous approach to institutional AI readiness—one that is uniquely suited to the governance and operational landscape of Ontario's community college system. The objectives outlined in the following section guide the development, validation, and application of this framework.

3.2 Operationalization of Theoretical Constructs

The study operationalizes institutional AI readiness through two interdependent theoretical constructs: Will, representing governance intent, and Way, representing implementation capacity. These constructs are grounded in organizational and pedagogical theory—specifically Constructivism, Connectivism, and the study's original extension, ConnectivAI, which accounts for the evolving interplay between learners, institutions, and intelligent systems in AI-enhanced educational environments.

To translate these theoretical constructs into measurable indicators, the research introduces the G-PLAC framework, a structured, multi-layered model designed to evaluate college readiness using evidence-based and reproducible methods:

- **Theoretical Layer – Pedagogical Foundations.** This foundational layer draws from contemporary learning theories. Constructivism emphasizes learner-centered discovery; Connectivism highlights distributed knowledge and digital networks; and ConnectivAI extends these principles to include human-machine co-learning dynamics, positioning AI as both an object and agent of institutional learning.
- **Operational Layer – Applied Readiness Attributes.** This layer translates theory into measurable constructs through four core domains: Programs, Learners, Agreements, and Classification. These G-PLAC elements capture institutional performance using publicly available datasets, program directories, and policy alignment indicators (e.g., Strategic Mandate Agreements, PGWP eligibility). Together, they reflect the Way dimension of readiness.
- **Methodological Layer – Validation and Scoring.** To ensure rigor and transparency, this layer applies a deterministic scoring system. Governance (Will)

is assessed using rubric-based evaluations of publicly available AI policy artifacts, interpreted through a large language model (LLM). Operational data (Way) are analyzed using R-based statistical models and normalized to generate a composite readiness score.

The outcome of this process is the AI Transition Readiness Index (TRI)—a composite metric normalized to a provincial average of 100, enabling inter-institutional benchmarking and longitudinal performance tracking. The TRI thus converts abstract constructs into practical diagnostics, giving policymakers and institutions a transparent tool to measure, compare, and plan for AI integration.

Beyond its immediate application, the G-PLAC framework and TRI form the foundation for a scalable, sector-wide knowledge repository: the proposed Artificial Intelligence in Education Body of Knowledge (AI-EdBOK). This evolving reference architecture is designed to support AI governance, curriculum modernization, and strategic planning across postsecondary systems in the AI era.

3.3 Recapitulation of Research Purpose and Questions

The purpose of this study is to develop and validate a structured, reproducible framework for evaluating the readiness of Ontario's publicly funded community colleges to transition into the AI-driven era of Industry 4.0. By synthesizing pedagogical theory, policy analysis, and quantitative metrics, the research offers a model that operationalizes two core constructs: institutional intent ("Will") and implementation capacity ("Way"). Through this dual-lens approach, the study aims to provide an actionable diagnostic tool—the Transition Readiness Index (TRI)—to support institutional benchmarking, governance reform, and strategic planning in the context of AI adoption.

This purpose is guided by the need to bridge the existing gap between abstract AI-readiness frameworks and the applied needs of college administrators, faculty, and policymakers. The study contributes not only a methodologically rigorous assessment model but also a theory-informed foundation for advancing discourse in AI governance, education technology, and institutional transformation.

3.3.1 Primary Research Question. How can the transition readiness of Ontario's community colleges for adopting artificial intelligence in the context of Industry 4.0 be measured using a reproducible framework grounded in educational theory, governance policy, and operational data?

3.3.2 Sub-questions.

1. How can the constructs of "Will" and "Way" be operationalized to reflect institutional readiness for AI integration in the college sector?
2. What governance and implementation attributes most significantly influence variation in AI readiness scores among Ontario's colleges?
3. To what extent can deterministic large language model (LLM) evaluation be used to assess institutional governance structures and policy artifacts in a reliable and reproducible manner?
4. How do Ontario's community colleges compare to global exemplars in AI readiness, and what institutional gaps emerge from this benchmarking?
5. What are the implications of applying a theory-informed Transition Readiness Index (TRI) for long-term planning, curriculum design, and AI governance in the college sector?

3.4 Research Design

While this study introduces several original constructs—such as the G-PLAC framework, the Artificial Intelligence in Education Body of Knowledge (AI-EdBOK) the Transition Readiness Index (TRI), and the Will vs. Way model of institutional alignment—these are not created in a vacuum. Each is derived from, or inspired by, existing and proven frameworks commonly applied by practitioners across governance, quality assurance, and data science domains. These include the Project Management Institute's PMBOK (Khoshgoftar and Osman, 2009), the Design Thinking (Henriksen, Richardson and Mehta, 2017) methodology, Lean Six Sigma (Sunder and Antony, 2018), data science best practices, and the supervisory rigor of the International Monetary Fund (IMF).

While some of these models originate outside traditional academic publishing, they are routinely used by auditors, regulators, instructional designers, and data scientists in both public and private sectors. Their incorporation into this dissertation reflects the applied, practice-oriented nature of Doctor of Business Administration (DBA) research and reinforces the study's alignment with its central guiding question—practically interpreted as:

How ready are Ontario's community colleges in fulfilling the AI-related workforce and governance needs of Industry 4.0?

The research's grounding in empirical and historical methods is a means of establishing both the credibility of the concept and the relevance in practice. It not only offers a theoretical model of the research but also a real one that can be used to inform institutional policy model, sectoral benchmarking, and strategic transformation—goals that need both scholarly insight and practical tools working together.

3.4.1 Design Thinking. This study employs a Design Thinking methodology to structure the development and validation of a reproducible framework for assessing AI readiness in Ontario's 24 publicly funded community colleges. Design Thinking provides a problem-solving architecture built around five iterative stages—Empathize, Define, Ideate, Prototype, and Test—allowing the research to remain both theory-informed and practitioner-relevant (Henriksen, Richardson and Mehta, 2017).

- **Empathize:** The study began with a comprehensive literature review to understand institutional gaps in AI governance, curricular adaptation, and data readiness within the college sector.
- **Define:** The central research question was formulated to address the need for a reliable, scalable, and reproducible method of measuring AI transition readiness at the institutional level.
- **Ideate:** Educational theories—Constructivism, Connectivism, and the novel extension ConnectivAI—were aligned with the sub-questions to conceptually inform the G-PLAC framework. These theories shaped how the research interpreted teaching, learning, and system adaptation to AI.

- **Prototype:** A proof-of-concept version of the framework was piloted using the QS World Top 10 AI universities as global exemplars. These institutions provided the learning model through which attribute definitions, rubric calibration, and deterministic evaluation methods were initially tested and refined.
- **Test:** The validated framework was applied to Ontario's 24 colleges using a dual-track design that ensured methodological rigor through a combination of data science, governance analysis, and quality assurance tools.

3.4.2 Dual-Track Methodological Framework. This study's research design integrates two tracks that work in tandem to ensure comprehensive and credible AI readiness assessment:

Track 1: Data Collection–Deterministic Chatbot and R-Based Public Data Scraping. Track 1 focuses on gathering AI-related data from two primary sources:

- **Source A:** For governance dimensions, a deterministic chatbot was deployed to extract and score institutional AI policies and communications using structured rubrics.
- **Source B:** For operational attributes, public datasets—such as program catalogs, micro-credential offerings, and graduate employment reports—were analyzed using the statistical programming language R. This allowed systematic measurement across the G-PLAC attributes, including Programs, Classification of Instructional Program alignment.

This modular approach to data collection ensures flexibility: scraping is used where structured data is absent, and statistical methods are applied when standardized datasets are already available.

Track 2: Due Diligence–Lean Six Sigma and IMF Supervision Protocols. Track 2 applies a second layer of methodological scrutiny to validate the results obtained from Track 1:

- **Source A:** For governance evaluations, Lean Six Sigma tools—specifically Gage Repeatability & Reproducibility (Gage R&R), Monte Carlo simulation and the DMAIC (Define, Measure, Analyze, Improve and Control) framework—were used to test the reliability and consistency of the chatbot-generated rubric scores across multiple runs and conditions.

- **Source B:** For operational data, a supervisory model inspired by the International Monetary Fund's AML/CFT framework was employed. This approach introduced proportionality, structured oversight, and risk-tier logic to evaluate institutional variation, contextualize gaps, and support fair comparison across diverse college profiles.

In cases where data from Track 1 and Track 2 intersected—such as institutional claims about AI curriculum or staff training—a hybrid analysis was conducted to enable cross-validation and resolve discrepancies. This ensured that findings were not only reproducible but also analytically robust.

For easier identification, the tracks are further categorized as:

- Track 1A – Governance Data Collection (Chatbots and Rubrics)
- Track 2A – Governance Quality Assurance (Gage R&R and Monte Carlo)
- Track 1B – Operational Data Collection (R, Chatbot)
- Track 2B – Operational Quality Assurance (IMF AML/CFT methodology)

When policy documents are not accessible without institutional credentials, the institution receives a reduced transparency score. This decision is grounded in a core principle upheld throughout the research: information transparency and public accessibility are essential components of good governance.

3.4.3 Research Design Summary. The author chooses to use Design Thinking, dual-source data collection, and multi-level due diligence, making a remarkable, and unique research design that is a replicable model for institutional AI readiness evaluation. It has got the right measure of both theoretical depth and operational practicality, therefore, it can be adapted for both the scholarly advancement and institutional planning across all postsecondary education systems.

3.5 Full Population Sample

The population for this study comprises Ontario’s 24 publicly funded community colleges (I = 24) and their associated full-time equivalent (FTE) student body of 188,071 learners (S = 188,071), as reported by the Ontario Colleges Library Service (OCLS, 2024). These colleges serve diverse communities across the province and vary in size, mandate, language of instruction, and program offerings. Together, they form the cornerstone of Ontario’s workforce development system and are a critical focus for AI transition planning within the broader context of Industry 4.0.

The student population data reflect the FTEs (full-time equivalents) for Ontario public colleges, as provided to OCLS by Colleges Ontario. These FTEs are sourced from the Ministry of Colleges and Universities (MCU) and are based on Ministry-audited enrollment data from two years prior to when they are reported. This ensures data integrity and aligns the population definition with provincial standards used in funding and strategic planning.

Because the study aims to evaluate AI readiness at a sector-wide level, a census-based approach was adopted. All 24 institutions (I = 24) were included as unique units of analysis, eliminating the need for sampling and allowing direct institutional benchmarking. This full coverage enhances the reliability of ratio-based comparisons (e.g., AI program density per student, governance visibility per institution) and supports scalable insights for strategic planning.

In addition to the primary college population, the study employed a comparative prototype group—the QS World Top 10 AI universities—during the framework development stage. These globally ranked institutions were used to prototype and calibrate rubric-based scoring methods and to test the adaptability of the G-PLAC framework outside the Ontario context. However, they were not included in the final Ontario-specific scoring dataset.

By anchoring the analysis in both institutional scale and student impact, the study maintains relevance for both governance-level assessments and learner-centered policy planning.

3.6 Participant Selection

This study does not involve human participants in the traditional sense (e.g., students, faculty, or administrators) and deliberately excludes the use of surveys, interviews, or focus groups. Instead, it draws exclusively on publicly accessible institutional data, policy artifacts, and performance indicators collected from Ontario's 24 publicly funded community colleges (I = 24). Each institution serves as a unit of analysis and is evaluated based on observable governance signals and operational attributes—sources that are verifiable, reproducible, and aligned with data science standards.

This decision reflects both methodological discipline and ethical prudence. Perception-based data, such as that gathered through surveys or interviews, often carries risks of bias—especially social desirability, internal censorship, or public-relations filtering. By contrast, policy documents, curriculum maps, and open-access repositories provide uniform, audit-ready information. These sources better reflect what external stakeholders—such as prospective students, faculty, and employers—can evaluate when making decisions.

Moreover, the study explicitly gives lower scores to institutions that place AI governance information behind login walls or restricted portals. The institution's transparency score is diminished by the unavailability of policy documents without the use of institutional credentials. This choice is driven by an essential principle that has been maintained throughout the study: openness of information and public availability are indispensable elements of good governance. These dimensions matter not only for evaluation purposes but also for real-world decisions—such as faculty recruitment and student enrollment—where access to institutional AI policy and vision is increasingly influential.

The study consolidates its commitment to reproducibility, objectivity and the ethical aspects of the research by opting to exclude the participation of human subjects and by utilizing only the data that are external, machine-readable and openly accessible. In this context, participant selection does not refer to individuals but to the inclusion of institutional entities and the eligibility of data based on public visibility and verifiable origin.

3.7 Instrumentation

The research is based on an organized set of instruments deliberately made to collect, score, and validate the institutional data in both tracks that are integrated by methodology. The tools aim for operational consistency, transparency, and reproducibility, inspired by best data science practices and Lean Six Sigma quality assurance standards

3.7.1 Governance Evaluation Instruments (Track 1A). For the governance dimension, a deterministic chatbot was developed to extract and score institutional AI-related policy artifacts directly from each college's website. The chatbot uses rule-based scraping and deterministic prompts to identify references to AI use, governance structures, faculty/student guidelines, and academic integrity policies.

3.7.2 Governance Scoring Structure and Distribution of Weights (Track 1A). As illustrated in Table 3.7, the rubric comprises five primary criteria—Completeness, Clarity, Relevance, Transparency, and Practicality—each scored on a scale of 0 to 10, contributing up to 50 points in total. In addition, two adjustment factors allow for up to ±3 points each based on Content Quality and Institutional Posture. However, final Governance scores are capped at 50 points, ensuring comparability across institutions and avoiding artificial inflation due to adjustment bonuses. This dual-layer scoring system ensures both the quality and seriousness of institutional governance are reflected in the final Governance (G) score.

Table 3.7.2
Governance (G) Scoring Range and Adjustment Criteria (Capped at 50)

Criterion	Definition	Score Range
Clarity	Policy language is unambiguous, intelligible, and suitable for non-specialist audiences.	0 to 10
Completeness	Policy explicitly addresses all three stakeholder groups: students, faculty, and administrative staff.	0 to 10
Transparency	Policy or AI guidance is publicly accessible without requiring login credentials.	0 to 10

Relevance	Content meaningfully addresses AI-specific risks, use cases, or institutional priorities.	0 to 10
Accountability	A responsible enforcement body, named office, or compliance mechanism is clearly identified.	0 to 10
Adjustment Criteria (Total score after adjustment is capped at 50 to a minimum of 0)		
Adjustment Attribute	**Definition**	**Adj. Points**
Adj 1 – Content Quality	Evaluates depth, enforcement, and contextual relevance of the policy.	-3 to +3
Adj 2 – Institutional Posture	Measures organizational commitment (e.g., AI committee, faculty council).	-3 to +3

3.7.3 Governance Rubric-Based Evaluation Approach (Track 1A). To ensure consistency, transparency, and repeatability in scoring institutional AI governance artifacts, a detailed rubric was pre-loaded into OpenAI's deterministic evaluation engine. This rubric guided the chatbot's assessment of each institution's policy language, structure, accessibility, and governance posture. By embedding the rubric directly into the chatbot workflow, all evaluations adhered to a standardized decision protocol. To ensure deterministic scoring and eliminate evaluator bias, the full Governance (G) rubric was pre-loaded into OpenAI and used by the chatbot to assess each institution's AI governance artifacts. As illustrated in Table 3.7.3, the full scoring rubric used by the Governance (G) Chatbot was pre-loaded into OpenAI to allow automated evaluation across five core and two adjustment criteria.

Table 3.7.3
Governance Rubrics as Uploaded onto OpenAI for Governance Chatbot Assessment

Score	Short Description	Explanation with Examples
COMPLETENESS: 0-10 (Coverage of Institutional AI Use) Assesses the breadth of policy coverage across domains such as teaching, administration, privacy, and training requirements.		
+2	Independent AI Office or Task Force	Includes a dedicated AI governance body (e.g., separate from IT or embedded in academic policy). Example: "AI Oversight Committee" or "AI Governance Task Force".
+2	AI Literacy Required or Recommended	AI-related training is required for students or staff, or strongly encouraged. Example: "Mandatory AI Readiness module for new students".

+2	AI Used in Teaching & Learning	AI tools (e.g., ChatGPT, Grammarly) integrated into pedagogy. Example: "AI used to assist in research-writing assignments".
+2	AI Used in Administrative Processes	AI applied to scheduling, grading, HR, or data reporting. Example: "Chatbot handles student queries".
+2	Privacy/Security Policies in Place	Policy discusses data protection, consent, or detection tools. Example: "Use of Turnitin AI detection must follow student privacy rules".
CLARITY: 0-10 (Stakeholder-Specific and Intelligible Language) Evaluates how clearly the policy communicates AI expectations to students, staff, faculty, and third parties, and whether the policy has institutional standing.		
+2	Institution-Wide Policy	Policy is official, signed by leadership or passed by the governing body, and applies campus-wide.
+2	Department-Level Support	Departments are allowed or encouraged to tailor or expand on the policy. Example: "Each faculty may provide its own AI use standards".
+2	Guidelines for Students	AI usage rules are explicitly provided to students. Example: "Students must cite AI use in assignments".
+2	Guidelines for Staff	Staff receive specific instructions or training on AI. Example: "Faculty are advised to avoid blanket bans".
+2	Guidelines for Contractors	External vendors and third parties are encouraged to adhere to AI policies. Example: "External proctors must abide by AI detection policy".
RELEVANCE: Choose One (Institutional Stance on AI Adoption) Measures how the institution positions AI—whether as a threat, a tool, or a strategic priority—with nuanced scores based on tone and implementation readiness.		
10	Embraced	AI is positioned as a positive innovation to be integrated institution-wide.
8	Encouraged	AI use is supported with guidance and caution.
6	Deferred	AI policy decisions are delegated to instructors or units to decide.
4	Discouraged	AI use is permitted but generally frowned upon.
2	Penalized	AI use leads to penalties (e.g., grade deduction).
0	Prohibited	AI use results in expulsion or is fully banned.
TRANSPARENCY: 0–10 (Public Visibility and Access) Assesses how easily the public and institutional community can find, access, and interpret the policy, including homepage visibility and public links.		
+2	Visible on Homepage	AI policy or topic appears on the institution's homepage, either as a direct link, in visible news, or accessible via a homepage search field.
+2	Public Access	AI policy is publicly accessible without login.

+2	Included in Handbook	Mentioned in student or staff handbook.
+2	Detection Tool Guidelines	Clear stance on detection tools. Example: “Turnitin AI Detection is discouraged”.
+2	Support Line	Email, hotline, chatbot, or contact form for AI-related inquiries.
PRACTICALITY: 0–10 (Policy Implementation and Support) Measures whether the institution provides concrete support, infrastructure, and AI-related academic or operational tools to implement the policy effectively.		
+2	Active Enforcement	Policy includes audit, penalty, or escalation mechanism. Example: “Violations reviewed by Academic Integrity Office”.
+2	Infrastructure Support	Network, devices, or platforms enable AI usage.
+2	Enhanced Tool Access	Grammarly, ChatGPT, Copilot or similar tools are permitted.
+2	GenAI Access for Students	Students can use institution-provided GenAI tools.
+2	AI Course Offerings	Formal courses or modules on AI, ML, or Ethics in AI.
ADJUSTMENT 1: Content Quality Rewards or penalizes institutions based on the depth, clarity, enforceability, and contextual tailoring of their AI policy documents.		
+3	Outstanding	Enforceable, innovative, detailed, and tailored.
+2	Strong	Clear, institutionally aligned, with real examples.
+1	Good	General policy with some relevant detail.
0	Neutral	Neither weak nor strong; boilerplate or minimal.
–1	Weak	Ambiguous or inconsistent. Policy is somewhere, but cannot be easily found.
–2	Vague	Lacking detail or enforceability.
–3	Superficial	Token gesture or borrowed with no local relevance.
ADJUSTMENT 2: Institutional Posture Evaluates organizational commitment—whether AI governance is handled by leadership, delegated, or avoided—and assigns merit or demerit accordingly.		
+3	Leadership	Oversight committee, faculty council, or senate AI policy group in place. Example: “AI policy passed by Senate”. 34
+2	Internal Review	AI governance reviewed yearly or tracked through official channels. 35
+1	Signals Seriousness	AI is part of a formal digital strategy or transformation initiative. 36
0	No Signal	No visible effort to own AI governance. 37
–1	Instructor-Only	Responsibility is delegated only to individual instructors. 38

–2	Relies on Others	Relies solely on outside associations (e.g., EDUCAUSE, CAI) with no local interpretation. 39
–3	Avoidance	Disavows responsibility entirely or defers to government control with no institutional policy. 40

3.7.4 Governance Validation and Framework Alignment Instruments (Track 2A). To substantiate the credibility and strength of the scoring system, two quality assurance techniques were utilized for the Governance probe:

- **Gage Repeatability & Reproducibility (Gage R&R):** This method was implemented to evaluate the variance of the chatbot scoring among the duplicated runs and document architectures. It ensured that governance evaluations were stable even when HTML structure, formatting, or URL encoding varied, thus minimizing scoring drift caused by extraction artifacts.
- **Monte Carlo Simulation:** This technique was used to simulate a realistic distribution of governance and operational scores across thousands of iterations. The ultimate goal of a Sigma was to represent overall value or Sigma for the framework as its statistic quality and variability resilience. Monte Carlo analysis verified that the framework was able to agree with the high performance in the simulation trials, thus enabling utilization for institutional benchmarking and strategic planning.

Additionally, a rubric codebook was maintained to standardize definitions and ensure consistent application of scoring rules across all institutions.

3.7.5 Operational Data Instruments (Track 1B). The second instrumentation stream processes operational attributes using scripts developed in the R programming language. These tools extract structured data from public sources such as statistic datasets, program catalogs, institutional reports, micro-credential databases, and graduate employment dashboards. As illustrated in Table 3.7.5, each of the G-PLAC attributes (Governance, Programs, Learners, Strategic Mandate Agreements and Classification of Instructional Programs codes) is scored using predefined criteria, then normalized for cross-institutional comparison.

Output from this stream is used to construct the AI Transition Readiness Index (TRI), a composite score anchored to a provincial average of 100. Scores are stored in structured Comma Separated Value (CSV) files, supporting auditability and enabling reanalysis or future replication.

Table 3.7.5
Operational PLAC Variable Definitions and Collection Methods

Variable	Description	Data Type	Collection Method	Normalized Label
Programs (P)	Number of AI-focused programs offered by each institution based on Government of Canada's Classification of Instructional Programs (CIP).	Public datasets	R	P_{norm}
Learners (L)	Percentage of full-time equivalent students enrolled in AI programs at each institution, based on CIP classifications.	Public datasets	R	L_{norm}
Agreements (A)	Presence and thematic alignment of Strategic Mandate Agreements (SMAs) with provincial AI priorities such as digital learning, innovation, and workforce development.	Ministry of Colleges and Universities	Chatbot	A_{norm}
Classification (C)	Degree of alignment between institutional AI programs and federal frameworks governing workforce, funding, and immigration policy (e.g., PGWP eligibility and NOC classification).	Public datasets	R	C_{norm}

3.7.6 Operational Scoring Structure and Distribution of Weights (Track 2A). The operational scoring structure evaluates institutional capacity through four distinct variables aligned with the G-PLAC framework: Programs, Learners, Agreements, and Classification. These variables collectively represent the Way dimension of the AI Transition Readiness Index (TRI), accounting for 50% of the total composite score.

Each G-PLAC variable captures a specific aspect of institutional readiness to implement and sustain AI integration in postsecondary education. To enable fair comparison across colleges—regardless of size, enrollment, or program count—each variable is normalized using statistical techniques. The resulting values are then weighted according to a predetermined distribution and aggregated into a single operational readiness score.

Table 3.7.6 below defines each variable, its purpose, and the corresponding weight applied in the TRI model:

Table 3.7.6
G-PLAC Variables and Equal Weights in TRI Operational Score

Attribute	Variable Label	Definition	Weight (%)
Programs	P_{norm}	Number of AI-focused programs offered, based on CIP classification.	25
Learners	L_{norm}	Percentage of full-time equivalent students enrolled in AI-related programs.	25
Agreements	A_{norm}	Presence and alignment of Strategic Mandate Agreements (SMAs) with provincial AI priorities.	25
Classification	C_{norm}	Count courses with unique CIP codes offered by an institution reflecting the variety of AI programs offered aligning with federal frameworks (e.g., NOC codes, PGWP eligibility).	25
Sub-total			100% (Operational Score = 50% of TRI)

The four attributes of the G-PLAC framework—Programs, Learners, Agreements, and Classification—represent core operational pillars of institutional AI readiness. By assigning equal weight (25%) to each variable, the scoring structure ensures analytical neutrality and simplifies interpretability across institutions. This design choice acknowledges that these domains are mutually reinforcing and must evolve in parallel to support holistic and sustainable AI integration.

The decision to adopt equal weighting avoids privileging any single input and aligns with the study's emphasis on methodological transparency and reproducibility.

This approach reflects the systemic nature of operational readiness, where institutional programs, student participation, policy alignment, and workforce relevance interact as co-dependent signals of maturity.

Sensitivity analysis, presented in Section 3.9.2, confirms the robustness of the equal-weighted G-PLAC model. TRI scores remained stable under perturbation, validating the empirical soundness of the equal distribution scheme. The analysis supports the use of a uniform weighting strategy to enable fair, scalable, and longitudinal benchmarking of AI integration across Ontario's community colleges.

3.7.7 Operational Validation and Framework Alignment Instruments (Track 2B). This study draws supervisory alignment from the International Monetary Fund's AML/CFT oversight framework—not for its content, but for its methodological structure. Specifically, the principles of risk-based supervision, institutional tiering, and proportionality are adapted to the educational context. Colleges are stratified based on their composite TRI scores and their position in the Will–Way quadrant. Institutions exhibiting low governance (Will) or weak operational capacity (Way) are not penalized but earmarked for diagnostic support and roadmap recommendations.

This supervisory logic ensures that the G-PLAC framework functions not only as a benchmarking tool, but also as a strategic guidance system, aligned with the regulatory best practices used in high-stakes financial systems. The use of deterministic evaluation rubrics mirrors the structured inspection tools deployed by IMF auditors, enabling transparent, auditable scoring without subjective interference.

Governance, as illustrated in Table 3.7.7 is a first-order control function: institutions are judged not only by what they do, but by how formally, transparently, and accountably they operate. In the G-PLAC model—aligned with the IMF's supervisory structure—governance acts as a supervisory lens. It does not merely sit as one attribute among others but functions as a control overlay that influences the interpretation of all operational indicators. An institution with weak governance, regardless of its technological or curricular advancement, is considered structurally fragile in the AI transition. Conversely, strong governance elevates the reliability of institutional claims and mitigates systemic risk.

Table 3.7.7
How G-PLAC framework aligns with IMF's AML/CFT Supervisory Rigor

Governance Score Tier	IMF Analogue	PLAC Interpretation
45-50	Strong Internal Controls	Trusted institution; may serve as a model for systemwide best practices
30-44	Satisfactory Governance	Moderate risk; progress should be monitored with evidence of follow-up
Below 30	Control Weakness	High-risk posture; operational claims require independent verification

IMF AML/CFT Concept	Education/PLAC Equivalent
Comprehensive governance audit	Institutions are judged not only by what they do, but by how formally, transparently, and accountably they operate.
Risk-Based Supervision	AI Readiness supervision based on TRI scores or quadrant (Will–Way) profile.
Tier Classification (1–3)	Tier 1 = Leaders, Tier 2 = Aspirants/Executors, Tier 3 = Detached
Proportionality Principle	Colleges with low scores are not penalized but flagged for strategic support
Institutional Risk Profile	College AI maturity inferred from Governance + PLAC composite TRI score
Remediation Plans	Targeted guidance or roadmaps for improvement, e.g., AI literacy, faculty rubrics
Supervision Templates	Deterministic rubric = equivalent of IMF on-site inspection templates
Ongoing Monitoring	TRI recalculated annually, supporting longitudinal tracking

This supervisory interpretation of governance ensures that institutional scores are not viewed in isolation, but as integrated signals of structural readiness. The following instrumentation methods support consistent application of this logic across all PLAC dimensions.

3.8 Data Collection Procedures

This research employed a well-defined, digital, and ethical process for data collection that coincided with the dual-track method as described in the research design.

The data were all sourced from publicly available data, which gives the study a high degree of transparency, auditability and also effects consistency in the sample.

3.8.1 Data Collection Window. The data collection process occurred between February and June 2025, providing a five-month window to capture the most stable and institutionally endorsed information. This timeframe was strategically chosen to:

- Allow institutions to finalize updates and adjustments to their AI policies, curriculum listings, and operational metrics following the Fall 2024 semester.
- Avoid disruptions or partial data changes that might occur during the launch of the Fall 2025 academic cycle.
- Ensure sector-wide comparability, by freezing the data snapshot before new academic-year policies are introduced or legacy ones phased out.

This alignment with the Ontario academic calendar ensures that each institution is evaluated under equivalent temporal conditions, eliminating seasonal variation and promoting fairness in cross-college benchmarking.

3.8.2 Governance Artifact Collection (Deterministic Chatbot Pipeline). Governance data were collected using a custom-built deterministic chatbot, designed to crawl and extract AI-related content from each institution's public website. Notably, the chatbot itself was developed using Agile software principles—specifically Extreme Programming (XP). Instead of using a traditional human pair programmer, the researcher adopted ChatGPT as the paired coder, engaging in over 220 iterative builds during a rapid two-week development sprint. This approach enabled continuous code review, prompt-driven debugging, and structured co-development using Python. The "robotic coder," guided by wireframes and logical parameters defined by the human developer, efficiently produced a robust and reproducible scraping tool aligned with the principles of XP: simplicity, feedback, courage, and communication (Beck, 2000).

The final chatbot pipeline followed repeatable parsing logic to identify:

- AI usage policies and guidelines.
- Academic integrity statements related to generative AI.
- Staff, faculty, and student conduct documents mentioning AI.

- Web mentions of AI governance committees, task forces, or oversight bodies.

The bot was programmed to prioritize root-level domains and official policy repositories, excluding blogs, marketing content, or unauthenticated sources. When content was hidden behind login walls, a metadata flag was triggered, and a transparency deduction applied.

Extracted content was then scored using a rubric-based engine embedded in the chatbot. Because the model followed deterministic logic, it returned the same score for identical input, reinforcing reproducibility. Outputs were saved into structured files and further validated using Gage R&R and Monte Carlo simulation, as detailed in later sections.

The bot was used to prototype the study of the QS World Top 10 AI Universities on governance. Once the concept was proven, the bot was also used to deterministically drive the Gage R&R and Monte Carlo simulations, stabilizing and standardizing data harvesting. Once the prototype established the model, light calibration was made to navigate the Ontario landscape, where some colleges had non-standard website designs or stored information in PDFs. Python extensions such as BeautifulSoup and PyMuPDF (formerly known as fitz) were used to finetune the bot for Ontario scraping.

In parallel, Lean Six Sigma's 5S (Hirano and Talbot, 1995) framework—Sort, Set in order, Shine, Standardize, and Sustain—was deployed to govern the use of the chatbot and R-based pipelines during the PLAC (Way) data mining phase. This helped establish consistent scripting protocols, reduce variation in output structures, and ensure maintainable data harvesting procedures across institutions (Byrne, Lubowe, and Blitz, 2007).

3.8.3 Data Sources of Governance Artifact (Will). To establish methodological rigor and transferability, the Governance (G) Chatbot was first prototyped on the QS World Top 10 AI Universities. This initial phase validated—using the prototype chatbot Build 180F—the deterministic scraping logic and informed refinements to the pipeline. The full structure of data sources used in the prototype is presented in Appendix A.

Following successful validation, a calibrated chatbot—Build 204J-FullSafe—was deployed across all 24 Ontario community colleges to systematically extract AI governance artifacts. The calibration was necessary to help the chatbot navigate uniquely designed websites and PDF documents used by Ontario colleges. The rubrics used to determine the evaluation outcome remain the same. Details of the Ontario data collection are documented in Appendix B.

Tables 3.8.3A and 3.8.3B illustrate small excerpts of the data sources and the versions of the chatbot engines used for the web scraping for each cohort.

Table 3.8.3A
Sample Governance Prototype Data Sources of QS World Top 10 AI Universities (2024-2025)

University	Primary Source	Secondary AI-Policy Source	Type	Collection method (Chatbot version)
Massachusetts Institute of Technology	Home page	Guidance for use of Generative AI tools	Web	Build 180F
Carnegie Mellon University	Home page	AI at CMU	Web	Build 180F
University of California, Berkeley	Home page	AI in Teaching & Learning Overview	Web	Build 180F
…	…	…	…	…

Table 3.8.3B
Sample Governance Data Sources of Ontario Colleges (2024-2025)

College	Primary Source	Secondary AI-Policy Source	Type	Collection method (Chatbot version)
Algonquin	Home page	AI & Academic Integrity page	Web	ON-AI-G-Build-204J-FullSafe
Cambrian	Home page	Recommendations on AI & Academic Integrity PDF	Web	ON-AI-G-Build-204J-FullSafe
Canadore	Home page	SoTL 2025 Symposium page	Web	ON-AI-G-Build-204J-FullSafe
…	…	…	…	…

Full data source tables for both the QS World Top 10 AI Universities and Ontario's 24 public community colleges are provided in Appendices A and B, respectively. These tables document primary and secondary source links, AI policy locations, data types (HTML/PDF), and the deterministic Chatbot version used for collection.

3.8.5 Operational Data Collection (R-Based Public Dataset Mining). For the operational dimension (Way), data collection was conducted using custom R scripts applied to a range of open-access government and institutional datasets. The data pipeline focused on quantifying the four G-PLAC variables—Programs, Learners, Agreements, and Classification—based on reproducible logic and standardized inputs. Data sources included:

- Ministry-published enrollment and program datasets.
- Institutional micro-credential catalogs and course listings.
- Strategic Mandate Agreements (SMAs) published by the Ministry of Colleges and Universities (MCU).
- Public descriptions of academic programs linked to federal immigration and workforce classifications (e.g., PGWP eligibility, NOC codes).

Raw data were cleaned, wrangled, and scored according to variable-specific rules defined within the G-PLAC framework. Each institutional value was normalized against sector-wide benchmarks to enable cross-institutional comparison. Output tables were stored in CSV format and used to compute the Way score component of the AI Transition Readiness Index (TRI).

In particular, data for the Programs (P), Learners (L) and Classification (C) variables were derived from the 2023–2024 College Enrolment Headcount spreadsheet, published by MCU through Ontario's Open Data Catalogue. A custom R script—originally developed during the author's HarvardX Capstone Project in Data Science—was used to ingest, filter, and process this dataset. Although publicly available, the dataset does not support API integration; hence a manual download of the spreadsheet was performed prior to executing the analysis pipeline.

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3.8.6 Data Sources of Operational Attributes (Way). The operational dimension of the G-PLAC framework was evaluated using a combination of public government datasets, institutional documents, and AI-assisted content parsing. To maintain transparency and enable replication, each of the four quantitative variables—Programs, Learners, Agreements, and Classification—was derived from publicly accessible sources, ensuring consistency across institutions and minimizing subjectivity.

Key sources include the Ontario Ministry of Colleges and Universities (MCU), institutional websites, and federal immigration and labor policy documents such as those maintained by Immigration, Refugees and Citizenship Canada (IRCC). Data were collected manually or parsed using deterministic language models, then normalized and scaled for standardized presentation.

Table 3.8.6 summarizes the primary sources and data types used to evaluate each G-PLAC operational domain, supporting reproducibility and scalability of the AI Transition Readiness Index (TRI).

Table 3.8.6
Operational Data Sources of Ontario Colleges

Attribute	Description	Access Link	Data format
Programs (P)	Count and proportion of AI-related programs offered by each institution, based on CIP classification.	Ontario Open Data Catalogue – College Enrolment	.xlsx (manual download)
Learners (L)	Percentage of full-time equivalent (FTE) student enrollment in AI-classified programs, matched to CIP codes	Ontario Open Data Catalogue – College Enrolment	.xlsx (manual download)
Agreements (A)	Thematic alignment of each college's Strategic Mandate Agreement (SMA) with provincial AI priorities (2020–2025).	College and University Strategic Mandate Agreements, 2020-2025	Chatbot
Classification (C)	Percentage of unique CIP codes covered by AI-related courses offered, reflecting relevance to PGWP/NOC frameworks.	Ontario Open Data Catalogue – College Enrolment	.xlsx (manual download)

3.8.7 Data Integrity Protocols. To protect against misclassification and false positives:

- All chatbot extractions were manually verified for URL validity and content structure.
- PDF-based policies were parsed using automated text extraction, and where PDF text was inaccessible (e.g., image-only scans), a fallback logic noted the parsing failure, attempted an optical character recognition (OCR) scan, and adjusted scoring accordingly.
- R-based scraping pipelines included exception handling routines to identify missing data and ensure data completeness across all institutions.

In cases where content was ambiguous or inconsistent across sources (e.g., a course catalog indicating AI training not reflected in institutional strategy documents), a hybrid review was conducted. The most conservative score was retained unless triangulated confirmation supported an adjustment.

3.8.8 Ethical Considerations. This study is based exclusively on publicly available data. All information is sourced from institutional websites, government dashboards, or open-access educational datasets. No private, sensitive, or personally identifiable information Tri-Council Policy Statement (PII) is collected. As such, the research qualifies as non-human subjects' research and does not require Research Ethics Board (REB) approval.

This classification is consistent with Canada's Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), which explicitly exempts research that relies solely on public data from requiring ethics review (Canada, 2022). If required by the university, an ethics exemption form will be submitted to confirm compliance prior to final publication or dissertation defense.

Nonetheless, the study adheres to the following ethical principles:

- **Transparency:** All scoring methodologies, rubrics, prompts, and evaluation criteria are fully documented and reproducible by other researchers.
- **Non-maleficence:** The study does assign institutional rankings through the Transition Readiness Index (TRI) for the purpose of sector-wide benchmarking. However, no individual senior academic leader, faculty, staff, or student is named, evaluated, or profiled. The rankings are used

diagnostically to inform policy and improvement—not to stigmatize or penalize institutions.

- **Attribution and Fair Use:** All external data sources, government datasets, and institutional materials are cited according to academic standards. All derived metrics and frameworks—such as G-PLAC, TRI, and AI-EdBOK—are original to the researcher and attributed accordingly.
- **Green Programming**: The study follows sustainable computing practices by minimizing computational waste. All data scraping and scoring tasks were scripted using resource-efficient code, executed in batch processes to reduce energy load. Large simulations (e.g., Monte Carlo runs) were optimized to avoid excessive redundancy and were only run as needed to confirm stability. This approach aligns with the growing movement toward environmentally responsible AI and data science research.

By anchoring the intellect with ethics, the research encompasses not only the academic integrity but also the autonomy of the institution during the progress of a data-driven insight into the changing role of AI governance and readiness in higher education.

3.9 Data Analysis

The data analysis strategy is structured to accommodate the dual-track nature of the study—balancing deterministic governance scoring with quantitative operational analysis—while ensuring transparency, reproducibility, and methodological rigor.

3.9.1 Data Normalization and Sensitivity Testing. To ensure equitable comparisons across Ontario's diverse community colleges, all raw scores derived from the G-PLAC framework were normalized to a common scale. This step was necessary because the input variables—ranging from student enrollment and program counts to rubric-based governance scores—exist on different measurement scales and unit types. Without normalization, larger institutions could appear to outperform smaller ones based solely on size, rather than proportional readiness or strategic intent.

Midpoint normalization was applied to scale each variable relative to the central tendency of observed values across all colleges. Instead of compressing values into a 0–1 range, this approach centers each score around the provincial midpoint, allowing institutions to be evaluated based on their divergence from the average rather than from extreme outliers. These normalized scores were then weighted according to the distribution logic defined in Sections 3.7.2 and 3.7.6 and used to calculate each institution's composite contribution to the Transition Readiness Index (TRI).

To evaluate institutional alignment with AI strategy as expressed in the Strategic Mandate Agreements (SMAs), the study developed a deterministic rubric focused on five core dimensions: strategic AI commitment, AI-related programming, workforce alignment, applied research, and community partnerships. Each dimension was scored on a scale from 0 to 10, with optional adjustment points for institutions that embedded AI in KPIs, interdisciplinary applications, or capital investment plans. This rubric was applied manually to all 24 SMA documents, with scores contributing to the "A" attribute in the G-PLAC operational framework. The rubric was designed to avoid overlap with Governance scoring, focusing instead on executional intent and operational planning.

Table 3.9.1
AI Alignment Rubric for Strategic Mandate Agreement (SMA) Scoring–G-PLAC Attributes

Dimension	Description	Score Range
1. Strategic AI Commitments	Mentions AI, automation, or digital transformation as part of strategic institutional goals.	0–10
2. AI-Related Program Goals	Describes current or planned AI/ML/data science programs or micro credentials.	0–10
3. Skills & Workforce Planning	Links AI education to job market needs, future workforce demand, or employer partnerships.	0–10
4. Applied Research in AI	Describes AI as part of innovation, applied research, grant proposals, or institutional R&D.	0–10
5. Community or Industry Partnerships	Mentions AI-related partnerships with industry, community, or public sector actors.	0–10
Adj +1: AI in KPIs	AI is explicitly included in the SMA's Key Performance Indicators or target outcomes.	+1
Adj +1: Interdisciplinary AI Integration	AI is described in connection with cross-disciplinary applications (e.g., AI in health/trades).	+1
Adj +1: AI Funding or Capital Planning	AI is linked to specific revenue goals, grant proposals, or infrastructure planning.	+1

This rubric defines the five core dimensions used to evaluate each Ontario college's alignment with artificial intelligence (AI) strategy as articulated in its Strategic Mandate Agreement. Each dimension is scored on a scale from 0 to 10 based on strength of commitment, specificity of planning, and institutional follow-through. Three additional adjustment criteria award bonus points (+1 each) for the inclusion of AI in performance metrics, interdisciplinary integration, or capital/funding plans. The rubric ensures scoring consistency and prevents overlap with Governance-based policy analysis.

Scoring Interpretation for Table 3.9.1. Each dimension of the rubric is scored using fixed anchors: 0, 2, 4, 6, 8, and 10, reflecting increasing levels of institutional alignment with artificial intelligence (AI) strategy as expressed in the Strategic Mandate Agreement (SMA). The following interpretations guide the deterministic scoring process:

- **0 points – Absent.** No mention of AI, automation, digital transformation, or related strategic themes in the given dimension.
- **2 points – Incidental.** Indirect or passing references to technology or innovation without clear linkage to AI. No actionable plans or strategic intent observed.
- **4 points – Emerging.** AI is explicitly referenced, but institutional engagement is tentative or exploratory. Statements lack specificity or formal planning.
- **6 points – Developing.** Institutional plans for AI are evident, with mention of specific programs, partnerships, or initiatives. Scope may be limited or preliminary.
- **8 points – Integrated.** AI is positioned as a defined institutional priority with supporting structures (e.g., dedicated funding, measurable goals, or interdisciplinary integration).
- **10 points – Exemplary.** AI is embedded across the institution's strategic and operational agenda, supported by detailed implementation plans, timelines, performance metrics, and cross-sectoral alignment.

These guidelines were implemented using a deterministic LLM-based evaluation framework, which applied the rubric consistently to each SMA extract. Where institutional language was ambiguous, the scoring model defaulted to the conservative end of the relevant scoring band. This approach ensures that higher scores reflect not only strategic intent, but also operational clarity and institutional commitment.

3.9.2 Deterministic SMA Scoring Logic for G-PLAC Attribute A. To evaluate institutional alignment with artificial intelligence (AI) strategy as expressed in the Strategic Mandate Agreements (SMAs), the study employed a deterministic rubric-based scoring method. Rather than invoking a language model multiple times, as was done in the Governance (G) dimension to assess policy reproducibility, this analysis applied a single-pass rule-based evaluation to each SMA. The decision to score each institution only once reflects the nature of the artifact being assessed: the SMA is a fixed, formal document negotiated with the province, and not subject to interpretation volatility. As such, statistical sampling was unnecessary.

The scoring rubric for Attribute A (Agreement) in the G-PLAC operational framework was hardcoded directly into the evaluation script using conditional logic and keyword matching. The rubric consisted of five primary dimensions—strategic AI commitment, AI-related programming, workforce alignment, applied research, and community partnerships—each scored on a 0–10 scale using fixed anchor values (0, 2, 4, 6, 8, 10). Additional adjustment points were awarded for explicit references to AI in institutional KPIs, cross-disciplinary initiatives, or capital planning.

This approach avoided prompt-based subjectivity by ensuring that each SMA was evaluated using the same deterministic logic path. The resulting scores were treated as raw inputs into the TRI model and normalized using the midpoint method described in Section 3.9.1.

3.9.3 Normalization Procedure. The normalization process was revised from a traditional min–max method to a midpoint normalization approach to better reflect institutional variance around the central provincial tendency rather than extreme values. The updated procedure follows these steps:

1. **Raw score collection:** Each institution's original value for a given attribute (e.g., number of AI courses) was gathered from structured datasets or validated web sources.

2. **Provincial midpoint calculation:** For each G-PLAC component, the midpoint was determined by averaging the minimum and maximum observed values across all 24 Ontario colleges.
3. **Midpoint normalization formula:** Each raw value was then rescaled using the following revised formula:

$$\textbf{Normalized Value} = \frac{\textbf{Raw Score} \times \textbf{100}}{\textbf{(Provincial Maximum + Provincial Minimum)/2}}$$

This formula generates a standardized score relative to the provincial midpoint, enabling meaningful comparison across institutions. Because values are scaled using the midpoint rather than range boundaries, normalized scores may fall above or below 100, reflecting institutional divergence from the provincial center. The resulting values were subsequently weighted according to the distribution logic defined in Sections 3.7.2 and 3.7.6 to compute each institution's composite contribution to the Transition Readiness Index (TRI).

3.9.4 Interpretation of Governance Weighting Hypotheses. To assess the robustness of the AI Transition Readiness Index (TRI), a sensitivity analysis was conducted across five weighted models in which the governance component ("Will") was assigned values of 20%, 30%, 40%, 50%, and 60%, respectively.

The remaining proportion of the score was evenly distributed among the four "Way" variables defined in the G-PLAC framework: Programs, Learners, Agreements, and Classification. The analysis used two colleges representing relatively high and low performance profiles. Results demonstrated that the normalized TRI scores for both institutions remained remarkably stable across all five weighting configurations. For example, the TRI score for College A ranged narrowly from 113.93 to 113.21 as the governance weight increased from 20% to 60%.

This minimal variation indicates that the TRI model is not overly sensitive to moderate changes in the weighting of its governance dimension. These findings validate the model's internal consistency and support the use of an equal 50/50 distribution between governance and operational components as a theoretically balanced and empirically sound default. Moreover, the normalization step plays a critical role in dampening the effect of input weight shifts, ensuring comparability across institutions.

Table Set 3.9.4
TRI Stability Under Varying Governance Weighting Scenarios (20%–60%)

Governance at 20% Weight					
Attribute & Normalized Index	Weight (%)	Coll. A	Norm. A	Coll. B	Norm. B
G	20	45	22.50	35	17.50
P	20	8	22.86	6	17.14
L	20	8	22.86	6	17.14
A	20	8	22.86	6	17.14
C	20	8	22.86	6	17.14
TRIraw	100	77		59	
TRInorm	**100**		**113.93**		**86.07**

Governance at 30% Weight					
Attribute & Normalized Index	Weight (%)	Coll. A	Norm. A	Coll. B	Norm. B
G	30	45	33.75	35	26.25
P	17.5	8	20.00	6	15.00
L	17.5	8	20.00	6	15.00
A	17.5	8	20.00	6	15.00
C	17.5	8	20.00	6	15.00
TRIraw	100	77		59	
TRInorm	**100**		**113.75**		**86.25**

Governance at 40% Weight					
Attribute & Normalized Index	Weight (%)	Coll. A	Norm. A	Coll. B	Norm. B
G	40	45	45.00	35	35.00
P	15	8	17.14	6	12.86
L	15	8	17.14	6	12.86
A	15	8	17.14	6	12.86
C	15	8	17.14	6	12.86
TRIraw	100	77		59	
TRInorm	**100**		**113.57**		**86.43**

Governance at 50% Weight					
Attribute & Normalized Index	Weight (%)	Coll. A	Norm. A	Coll. B	Norm. B
G	50	45	56.25	35	43.75
P	12.5	8	14.29	6	10.71
L	12.5	8	14.29	6	10.71
A	12.5	8	14.29	6	10.71
C	12.5	8	14.29	6	10.71
TRIraw	100	77		59	
TRInorm	**100**		**113.39**		**86.61**

Governance at 60% Weight					
Attribute & Normalized Index	Weight (%)	Coll. A	Norm. A	Coll. B	Norm. B
G	60	45	67.50	35	52.50
P	10	8	11.43	6	8.57
L	10	8	11.43	6	8.57
A	10	8	11.43	6	8.57
C	10	8	11.43	6	8.57
TRIraw	100	77		59	
TRInorm	**100**		**113.21**		**86.79**

As evident in Table Set 3.9.4, even with a significant 30% increase in the weight of Governance and a reduction in the PLAC indices, the overall impact on the Normalized TRI scores is relatively small. The experiment suggests that the TRI is relatively sensitivity-proof to variations in the weighting scheme, demonstrating a balance between robustness and consistency.

3.9.5 Data Structuring Using the KCS Framework. To manage the transition from unstructured or semi-structured data into actionable institutional insights, the study applied principles from the Knowledge-Centred Service (KCS) framework (Tang, et al., 2020). Originally designed for dynamic knowledge environments, KCS emphasizes structured data capture, refinement, reuse, and iterative improvement. These principles were applied to both governance artifacts and operational datasets in the following ways:

- **Capture and Structure:** Data from web scraping and public repositories was immediately organized into tagged formats for scoring.

- **Reuse:** Standardized rubrics and codebooks enabled consistent interpretation of recurring governance structures and policy language.
- **Improve:** Anomalies (e.g., inaccessible PDFs, multilingual content) triggered refinements to scraping logic and rubric adjustments.

KCS thus served as the underlying logic for transforming fragmented, distributed institutional data into a coherent, scalable knowledge base—ultimately supporting the development of the AI-EdBOK repository and the continuous evolution of the G-PLAC framework.

3.9.6 Hybrid Cross-Validation. Where governance policy claims were also observable through operational data (e.g., AI training mandates reflected in program catalogs), a hybrid validation approach was used. Scored outputs were cross-checked across tracks to resolve inconsistencies or signal deeper institutional gaps.

Through the combined operation of these analytical methods, it guarantees that the Transition Readiness Index (TRI) encompasses not only the methodological robustness but also the institutional reality, which is what makes it a unique tool for diagnosing, policymaking, planning, and research.

3.9.7 Strategic Classification Using the Will–Way Quadrant. To enhance interpretability and support strategic planning, each institution is plotted on a Will–Way matrix, modeled after the logic of the Eisenhower prioritization grid. In this framework:

- The **X-axis (Way)** reflects the institution's operational capacity, as measured through PLANET-X attributes (e.g., program integration, employment outcomes, digital infrastructure).
- The **Y-axis (Will)** reflects the strength of the institution's AI governance, policy transparency, and strategic intent.

This quadrant model enables intuitive visual comparison and supports system-level prioritization. Institutions fall into one of four typologies:

Table 3.9.7
Will—Way Quadrant Mapping (Eisenhower Grid Analogy)

	High Way (Strong PLAC Capabilities)	**Low Way (Weak PLAC Capabilities)**
High Will (Strong Governance)	**Leaders** Strong policy foundation and active delivery of AI-integrated education.	**Aspirants** Strategic intent is evident, but operational capacity lags.
Low Will (Weak Governance)	**Executors** AI capabilities exist without clear policy direction; risks of misalignment.	**Detached** Institution lacks both AI strategy and delivery capacity.

This classification system provides a powerful visual diagnostic that helps policymakers, researchers, and institutional leaders identify:

- Who is ready to scale AI implementation.
- Who needs operational or governance support.
- Where capacity-building efforts might yield the highest return.

3.9.8 Diagnostic Visualization Using Fishbone Diagrams. To identify root causes of institutional underperformance or variability in AI readiness, the study employed Fishbone Diagrams, also known as Ishikawa Models. These diagnostic tools support structured problem decomposition by visually mapping potential contributing factors across defined operational categories. Originally developed for quality management in industrial contexts, Fishbone Diagrams are adapted here to trace gaps in institutional capacity along dimensions aligned with the original PLANET-X model.

Each finbone isolates factors contributing to underperformance within the Way dimension of the AI Transition Readiness Index (TRI), organizing them into the following categories:

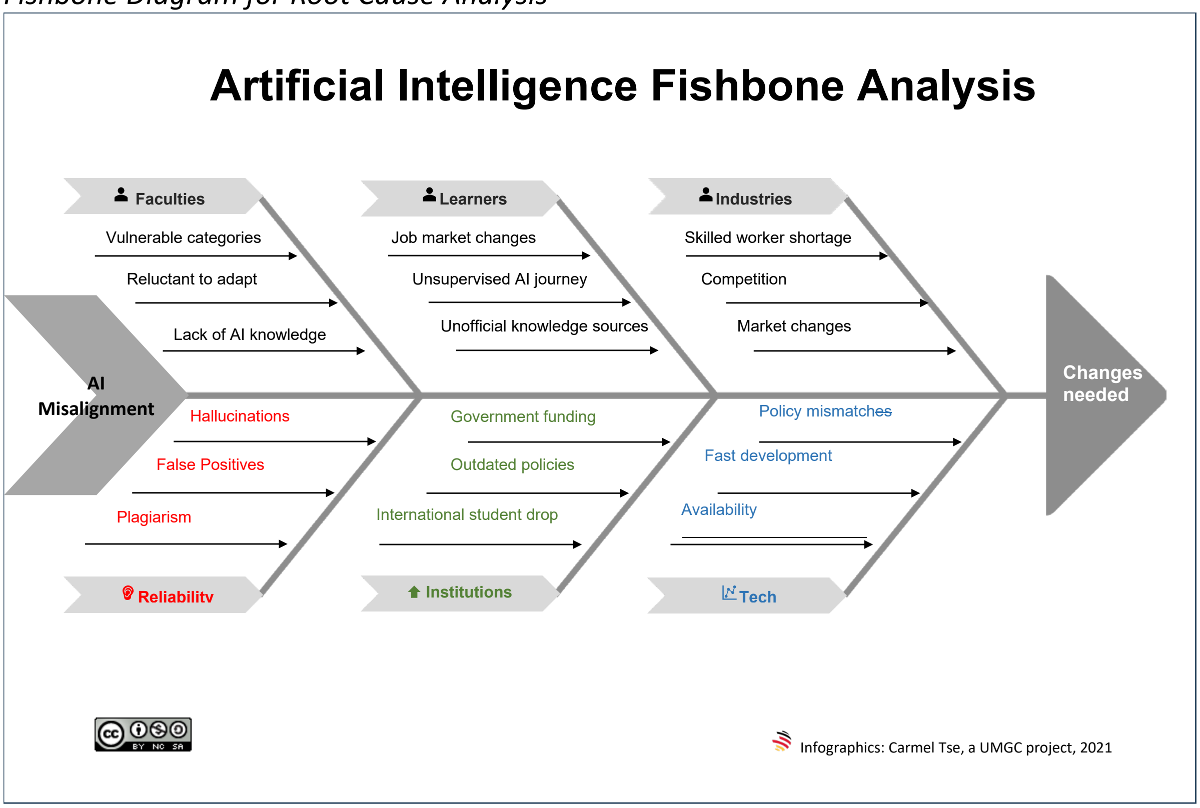
- **Governance** – e,g**.**, institution policies or the lack of them fail to provide directions to learners, faculties and sponsors.

- **Programs** – e.g., limited availability or specialization of AI-focused courses; outdated curriculum mappings.
- **Learners** – e.g., insufficient enrollment in AI programs; lack of outreach to underrepresented student populations.
- **Agreements** – e.g., deviation from legally binding mandates that affect funding.
- **Classification**– e.g., misaligned course offerings that fail the support of labour demands or immigration-intake goals.

Fishbone Diagrams are useful as an explanatory tool during early-stage diagnostics or institutional audits. By visually surfacing the interdependencies among root causes, these diagrams support data-informed decision-making and help institutions prioritize corrective strategies.

The fishbone diagrams serve as a visual diagnostic tool that complements numerical TRI scores and supports institution-specific recommendations in later chapters.

Figure 3.9.8
Fishbone Diagram for Root Cause Analysis



Although the current G-PLAC model consolidates operational variables for scoring purposes, legacy elements from the original PLANET-X framework—such as Academic Staff Support, Employment, and Technology—remain diagnostically useful. These categories can be retained as finbone problem indicators in root-cause analyses and visualizations to guide institutional improvement, even if they no longer scored as standalone attributes in the TRI.

3.9.9 Data Analysis Summary. Together, these analytical strategies ensure that the Transition Readiness Index (TRI) is more than a score—it is a diagnostic ecosystem, integrating structured data, validation tools, knowledge management logic, and strategic planning instruments. This comprehensive approach enables colleges, policymakers, and researchers to move from measurement to action in navigating the transition to AI-enhanced teaching and governance. These steps—normalizing data, adjusting attribute weights, and testing score stability—ensure that the TRI is both reproducible and theoretically grounded, aligning with the Will–Way model of institutional AI readiness.

3.10 Research Design Limitations

While this study introduces a structured and reproducible framework for evaluating AI readiness across Ontario's public colleges, several limitations must be acknowledged to situate the findings within appropriate analytical and methodological boundaries.

3.10.1 Dependence on Public Data. The study relies exclusively on publicly accessible data from institutional websites, government dashboards, and open educational datasets. While this enhances transparency and auditability, it also introduces constraints:

- Institutions that restrict key policies behind login walls or internal intranets receive lower transparency scores, regardless of whether such policies exist internally.
- Certain governance elements—such as informal working groups or emergent practices—may go undetected if they are not publicly documented.

This limitation reflects a deliberate ethical stance in favor of information transparency, but it may underrepresent internal progress made by more opaque institutions.

3.10.2 Web and PDF Parsing Limitations. Despite robust deterministic scraping logic, the accuracy of data capture is limited by:

- Non-standard website structures.
- Poorly formatted or image-based PDFs that resist machine parsing.
- Institutional redesigns or dead links during the data collection window.

While fallback procedures and manual checks were implemented, parsing failures may have introduced minor data loss or under-scoring in isolated cases.

3.10.3 Absence of Qualitative Institutional Context. The study excludes interviews and surveys to minimize bias and maximize reproducibility by design. However, this also limits the ability to account for institutional nuance, intent, or internal efforts that have not yet manifested in public-facing outputs. Consequently, the results reflect what institutions show, not necessarily what they know or plan.

3.10.4 Temporal Snapshot and Policy Volatility. Data collection occurred between February and June 2025, deliberately timed to avoid transitional periods in the academic cycle. Nevertheless, institutional AI policies and programs may evolve rapidly—particularly in response to regulatory shifts or public scrutiny. As such, findings represent a snapshot rather than a longitudinal trajectory.

3.10.5 International Generalizability. The framework was prototyped using QS World Top 10 AI universities and applied to Ontario's 24 colleges. While scalable, the tool has not yet been fully validated across institutions outside this geographic or policy context. Further research is required to test the model's adaptability across provinces, countries, or education systems with different governance architectures.

3.11 Research Methodology Conclusion

This chapter presented the methodological framework for evaluating institutional AI readiness across Ontario's 24 publicly funded community colleges. The study is grounded in a Design Thinking approach, operationalized through a dual-track system that separates data collection methods (via deterministic chatbots and R-based scripts) from due diligence validation (via Lean Six Sigma and IMF-inspired oversight logic).

In alignment with the study's emphasis on reproducibility and operational rigor, two additional methodological frameworks were applied during tool development and data processing. First, the Extreme Programming (XP) methodology guided the chatbot's creation, with ChatGPT serving as a paired coder across 220 iterative builds. This approach enabled rapid prototyping, real-time logic validation, and adherence to Agile design principles. Second, Lean Six Sigma's 5S framework (Sort, Set in Order, Shine, Standardize, Sustain) was deployed during the PLAC (Way) data mining phase to ensure consistent scripting practices and scalable data collection. These frameworks reinforced the study's dual goals: delivering an academically sound model and building tools robust enough for real-world benchmarking across diverse institutional contexts.

Key instruments—including fixed scoring rubrics, Monte Carlo simulations, and the Gage R&R method—were employed to ensure transparency, consistency, and statistical reliability. The integration of the Knowledge-Centered Service (KCS) framework further enhanced the study's ability to transform unstructured data into usable knowledge, contributing to the emerging AI-EdBOK repository.

The data collection window (February to June 2025) ensured sector-wide comparability while respecting academic calendar cycles. The ethical strategy of using only publicly available information ensures compliance with Canada's TCPS2 guidelines, and additional safeguards—including non-personal evaluation, green programming, and diagnostic framing—underscore the study's commitment to responsible research practices.

While acknowledging limitations related to policy visibility, parsing constraints, and the temporal scope of data, the methodology remains robust, reproducible, and well-aligned with both scholarly standards and real-world applicability.

Collectively, these design choices position the Transition Readiness Index (TRI) not merely as a scoring system, but as a diagnostic framework that informs planning, benchmarking, and system-wide improvement as institutions transition into the AI era.

CHAPTER IV:
RESULTS

This chapter presents the results of the study, structured around the two core constructs of the G-PLAC framework: Governance intent ("Will") and Operational capacity ("Way"). These results are derived from deterministic rubric-based evaluations, statistical normalization of public datasets, and benchmarking against global exemplars, specifically the QS Top 10 AI universities.

Section 4.1 addresses the first research question, analyzing institutional governance readiness through the lens of publicly accessible AI policies, ethical guidelines, and strategic documentation. This dimension is operationalized as the Governance (G) score, derived through a deterministic chatbot evaluation process validated with Gage Repeatability and Reproducibility (Gage R&R) and Monte Carlo simulations. Scores are interpreted using Sigma-level tiers and compared across all 24 Ontario colleges.

Section 4.2 turns to the second research question, which assesses operational readiness based on institutional program offerings, learner engagement, employment outcomes, technology access, and strategic alignment. These indicators form the PLAC variables—Programs (P), Learners (L), Agreements (A), Classifications (C)—and are combined to produce normalized scores that reflect each institution's implementation capacity.

Section 4.3 integrates these dimensions to map institutions into a Will–Way quadrant using an Eisenhower Matrix-style typology. Colleges are categorized as Leaders, Aspirants, Executors, or Detached, based on their positioning along governance and operational axes.

Finally, Section 4.4 synthesizes the findings, identifies cross-institutional patterns, and highlights outlier cases. It also prepares the foundation for Chapter V, which will interpret these results through theoretical and strategic lenses and propose practical pathways for institutional improvement and policy development.

Together, these results provide a robust, reproducible snapshot of AI transition readiness across Ontario's college system—one that enables both benchmarking and continuous improvement over time.

4.1 Research Question One: Governance (Will)

This section addresses the first research question:

RQ1: To what extent do Ontario's community colleges demonstrate governance readiness through formal policies, ethical guidelines, and strategic commitments to AI integration?

To operationalize this question, governance readiness was measured through the Governance (G) score, a reproducible index derived from rubric-based evaluations of publicly accessible institutional artifacts. The governance score reflects an institution's strategic intent ("Will") to engage with AI in a formal, transparent, and enforceable manner. Evaluation focused on five core criteria—Completeness, Clarity, Relevance, Transparency, and Practicality—supplemented by two adjustment factors addressing content quality and institutional posture.

All evaluations were conducted using a deterministic chatbot (Build 204J-FullSafe), which scraped institutional websites for AI-related policy signals and scored them against a standardized rubric uploaded to OpenAI. To ensure scoring reproducibility, 50 scoring trials per institution were performed and validated using Gage Repeatability and Reproducibility (Gage R&R) as well as Monte Carlo simulations. These validation steps confirmed minimal variance and high inter-run reliability, affirming that the results can be trusted for both benchmarking and longitudinal tracking.

4.1.1 Overview of Governance Scoring Outcomes: QS World Top 10 Benchmarking.

Governance (G) scoring began with an international benchmarking phase using the QS World Top 10 AI Universities. These globally recognized institutions served as the reference cohort to calibrate rubric interpretation and validate the deterministic evaluation framework. Governance scores among the Top 10 ranged from approximately 31 to 45 out of 50, with most institutions achieving stable, high-performance results across multiple rubric dimensions.

A subset of institutions—including Harvard, MIT, ETH Zurich, and the National University of Singapore—achieved Final scores above 40, reflecting comprehensive AI governance policies, clearly articulated enforcement structures, and transparent public-facing documentation. These institutions consistently scored in the upper Sigma tiers, with reproducibility confirmed through Gage R&R analysis and Monte Carlo simulations.

Conversely, institutions with lower Governance scores typically exhibited one or more of the following limitations:

- Fragmented or decentralized policy articulation
- Insufficient public transparency (e.g., inaccessible or non-indexed documentation)
- Limited operational clarity on AI tool use, enforcement, or support infrastructure
- General principles lacking specific references to AI governance

To enable standardized quality comparison, each university's Governance score was translated into a Six Sigma-inspired tier classification. Institutions scoring above 45 were placed in Tier 1 (Robust Governance Infrastructure); those between 35 and 44 were categorized as Tier 2 (Structured but Variable Governance); and those below 35 were classified as Tier 3 (Underdeveloped or Opaque Governance). This tiering system was subsequently applied to the Ontario colleges to maintain cross-cohort consistency.

4.1.2 Data Collection and Quality Assurance: Benchmarking with QS World Top 10. To ensure methodological reliability and mitigate provincial or institutional bias, the Governance (G) scoring system was initially deployed in a global benchmarking phase using the QS World Top 10 AI Universities (QS, 2024). This phase functioned as both a data collection pilot and a quality assurance protocol, enabling rigorous calibration of the deterministic chatbot-based evaluation system before its application to Ontario's community colleges.

Two core objectives guided this phase. First, it allowed for system validation in a high-governance environment—where AI policies are expected to be mature, transparent, and accessible—thereby establishing whether the rubric and deterministic logic could accurately and reproducibly differentiate institutional quality. Second, it established a normalized global baseline of Governance performance against which Ontario institutions could later be compared, ensuring external validity and benchmarking rigor.

Each of the Top 10 universities was evaluated 50 times using a temperature-zero setting to eliminate stochastic variability. The resulting dataset was subjected to Gage Repeatability and Reproducibility (Gage R&R) analysis and Monte Carlo simulations to assess scoring consistency, variance, and sigma tier stability. This multi-layered quality assurance process verified that the chatbot evaluation system could reliably extract, interpret, and score institutional AI governance content at scale, providing a defensible foundation for subsequent provincial deployment.

A suite of four Python-based Analytic AI chatbots was developed to execute this benchmarking process. All models were constructed under an Agile Extreme Programming (XP) framework, with deterministic logic enforced through OpenAI's GPT API (temperature = 0) to eliminate variance and ensure replicability.

- The **Rubrics Utility Bot** (See Appendix C) was designed to preload seven governance assessment rubrics (Table 3.2) into memory—Completeness, Clarity, Relevance, Transparency, Practicality, Adjustment 1 (merits), and Adjustment 2 (demerits). This minimized memory overhead and token consumption across runs, enhancing both efficiency and environmental performance.
- The **Bench-Build-180F – AI Governance Benchmarking Bot** (See Appendix D) conducted web scraping of institutional AI policy documents across the QS Top 10 list. Natural Language Processing (NLP) routines extracted structured text snippets, which were then evaluated using the preloaded rubric. All evaluations produced fully explainable outputs and rubric-justified scores.
- The **Six-Sigma-Parser-1– Analytic Stability Testing Bot** (See Appendix E) executed 50 independent evaluations per university to assess scoring consistency through Gage Repeatability and Reproducibility (R&R) testing. Key statistical indicators—mean, range, and standard deviation—were computed to identify variance levels in governance interpretation.
- The **Six-Sigma-Monte-Carlo-4 – Predictive Modeling Bot** (See Appendix F) modeled one million virtual evaluations per university by applying controlled ±7-point tolerance across rubric attributes. The output was converted into Defects Per Million Opportunities (DPMO) and categorized using Sigma Tier designations to reflect long-term evaluation stability.

The reproducibility test yielded a clear ranking in governance consistency. Institutions like Harvard University, MIT, and the National University of Singapore demonstrated near-perfect scoring reproducibility, with standard deviations under 1.0 and tight scoring bands. In contrast, schools such as Nanyang Technological University and the Hong Kong University of Science and Technology showed wider fluctuations, likely due to ambiguous or diffusely published policy artifacts.

Table 4.1.2A
QS World Top 10–Benchmarked Repeatability & Reproducibility Test Summary of 50 Runs Sorted by Standard Deviation

Institution	Final Score Range	Final Score Mean	Final Score Std. Dev
National University of Singapore	33–34	33.96	0.20
Harvard University	43–45	44.96	0.28
Massachusetts Institute of Technology	31–36	34.86	0.86
ETH Zurich	33–40	36.04	1.03
University of Toronto	41–47	43.52	1.55
University of California, Berkeley	35–40	37.26	1.61
Carnegie Mellon University	37–43	39.50	2.00
University of Oxford	33–41	36.38	2.52
Hong Kong University of Science and Technology	24–35	31.50	2.94
Nanyang Technological University	22–36	32.80	3.57
Overall	**22-47**	**37.08**	**1.66**

The resulting Sigma Tier classifications (Table 4.1.2B) showed that over half of these institutions maintained Six Sigma stability under simulated stress. Harvard, MIT, and NUS, for example, consistently scored above 43/50 and yielded DPMOs close to zero—suggesting that their AI governance policies were not only publicly accessible and comprehensive, but also structured in ways that minimized interpretation ambiguity across repeated evaluations.

Table 4.1.2B
QS World Top 10 –Monte Carlo Simulation Sorted by Sigma Value with Defects per Million for Quality Assurance (c= 1 mil) and a ±7 Aggregated Shift of ±1 for Each of the Seven Assessment Attributes

Institution	Avg. Final	Std. Dev.	DPMO	Sigma Value	Sigma Level
Harvard University	44.96	0.28	0	6.00	6σ
ETH Zurich	36.04	1.03	0	6.00	6σ
Massachusetts Institute of Technology	34.86	0.86	0	6.00	6σ
National University of Singapore	33.96	0.2	0	6.00	6σ
University of California, Berkeley	37.26	1.61	14	5.84	5σ
University of Toronto	43.52	1.55	12	5.72	5σ
Carnegie Mellon University	39.5	2	476	4.82	4σ
University of Oxford	36.38	2.52	5583	4.03	4σ
Hong Kong University of Science and Technology	31.5	2.94	17223	3.61	3σ
Nanyang Technological University	32.8	3.57	50031	3.14	3σ
Average	37.08	1.66	7333.90	5.12	5σ

While Table 4.1.2A ranks institutions by Standard Deviation to emphasize scoring consistency during the Gage R&R analysis, Table 4.1.2B presents institutions ordered by Sigma Tier to reflect their overall stability under large-scale simulation. This distinction is deliberate: the former isolates chatbot repeatability under controlled conditions, while the latter combines performance and variability to assess robustness using Six Sigma thresholds. Together, they offer complementary views on evaluation quality—precision and durability.

In addition to confirming reproducibility, this global benchmarking phase validated the objectivity of the scoring model before its application to Ontario colleges. These elite universities were not used as aspirational targets, but rather as calibration cases to ensure that the evaluation logic operated correctly across policy environments of high transparency and maturity.

This phase also demonstrated the feasibility of a deterministic, rubric-based scoring system as a form of Analytic AI—distinguished from Generative AI by its explainability, reproducibility, and policy alignment. Results from this benchmarking directly informed the scoring baselines, sigma tier thresholds, and diagnostic interpretations that underpin the rest of the study.

To document the benchmarking process with transparency and granularity, individual AI governance evaluation reports were generated for each of the QS Top 10 institutions using the deterministic Governance Chatbot (Build 180F). These reports provide detailed rubric-level scores, adjustment rationales, and diagnostic annotations grounded in the five core governance dimensions and two adjustment factors. From the 50 evaluation runs conducted per institution during the Gage R&R phase, the report selected for inclusion reflects the mode final score—that is, the score that occurred most frequently across all runs. This approach ensures that each institutional profile included in Appendix G represents the most statistically representative case and avoids the bias of selecting a high-performing outlier or anomalous result. Appendix G thereby complements the simulation-based validation by offering rubric-aligned, explainable exemplars for each benchmarked institution. A summary of the mode values and comparative performance data is provided in Appendix H.

To further validate the stability of the governance scoring methodology under conditions of high-frequency application, a Monte Carlo simulation was conducted using one million randomized evaluation events per institution. The results are visualized in Appendix I via two complementary plots: a histogram displaying the frequency distribution of final scores, and a Kernel Density Estimation (KDE) curve (Węglarczyk, 2018) illustrating the smoothed probability density. These visualizations demonstrate that institutions with mature AI governance frameworks—such as Harvard, MIT, and the National University of Singapore—exhibited not only high mean scores but also tight, unimodal distributions with low variability, reinforcing their classification as Six Sigma institutions. The use of KDE adds interpretive clarity by transforming discrete score frequencies into a continuous probability function, enabling readers to assess distributional symmetry, modality, and variance at a glance.

It is important to clarify that the sigma classifications used in this study are based on an augmented framework tailored specifically to AI governance scoring. Unlike traditional Six Sigma methods used in manufacturing, this model evaluates reproducibility by applying a ±7-point aggregate tolerance—one point per rubric attribute—across one million Monte Carlo simulations. Each simulation represents a plausible instance of scoring variability under real-world interpretation noise. Institutions whose simulated scores remained tightly clustered—exhibiting low standard deviation and minimal distributional spread—were classified at the "Six Sigma" tier within this context.

While this specific form of sigma ranking based on rubric-level DPMO has not appeared in published studies to date, it draws conceptual support from the broader Lean Six Sigma literature, particularly within the Define and Measure phases of the DMAIC cycle. As shown in recent research applying DMAIC to AI reliability and process optimization (Singh et al., 2022), contextual adaptation of variation thresholds and quality baselines is both common and encouraged. This study extends that logic by integrating deterministic AI scoring, a defined rubric structure, and probabilistic evaluation to construct a domain-specific benchmarking tool for assessing institutional AI governance maturity.

4.1.3 Institutional-Level Benchmarking Reports−QS World Top 10. To validate the deterministic rubric architecture and demonstrate its transferability across high-governance environments, institution-specific diagnostic outputs were generated for each member of the QS World Top 10 AI Universities. These reports include both quantitative scoring and narrative interpretation aligned to the modal score from the 50-run deterministic evaluation phase. Three appendices support this validation:

- **Appendix G** – Final Score Range, Mode, Sigma Tier and Best-Matched Report Run Date and Time.
- **Appendix H** – Human-readable, governance institutional summary and explanation based on mode-aligned final score.
- **Appendix I** – Monte Carlo simulation outputs, including the histogram and KDE curve visualizations used to assess scoring stability.

These appendices establish a rigorous benchmark against which other institutional cohorts—such as Ontario's 24 public colleges—can be comparatively assessed. Beyond rubric validation, these reports illustrate the interpretability and reproducibility of the scoring system and may serve as reference exemplars for institutions seeking to emulate global best practices in AI governance transparency.

4.1.4 Governance Ranking of QS World Top 10. While the previous two tables demonstrated reproducibility (Table 4.1.2A) and long-term stability (Table 4.1.2B) using statistical metrics, this section consolidates those insights into a single comparative ranking based on average final governance score. The institutions are sorted in descending order of mean Governance score, reflecting the strength and maturity of their publicly accessible AI policy infrastructure as evaluated under deterministic, rubric-based conditions.

Table 4.1.4 provides the final ordering used for benchmarking purposes in the remainder of the study. It serves as a global reference point for interpreting Ontario colleges' performance, particularly in highlighting institutional exemplars in AI governance policy completeness, clarity, transparency, and enforceability.

Table 4.1.4

QS World Top 10 –Governance Rankings Sorted by Score

Rank	Institution	Avg. Final Governance Score	Sigma Tier
1	Harvard University	44.96	6σ
2	University of Toronto	43.52	5σ
3	Carnegie Mellon University	39.50	4σ
4	University of California, Berkeley	37.26	5σ
5	University of Oxford	36.38	4σ
6	ETH Zurich	36.04	6σ
7	Massachusetts Institute of Technology	34.86	6σ
8	National University of Singapore	33.96	6σ
9	Nanyang Technological University	32.80	3σ
10	Hong Kong University of Science & Technology	31.50	3σ

4.1.5 Conclusion: Normalization and Governance Ranking with Rubric Components of QS World Top 10. To ensure transparency in scoring and comparability across institutions, the seven components of the Governance rubric were averaged across 50 deterministic runs for each institution. These components include five rubric pillars

(Completeness, Clarity, Relevance, Transparency, and Practicality) and two adjustment categories (Adj1 and Adj2). The average of these components provides both the raw Governance score and a normalized score indexed against the provincial and global cohort.

Midpoint normalization was performed to establish a baseline for middle of the range scores. The outcomes were further scaled for the average scores to be at a baseline index of 100, corresponding to the average, in this case, Final Governance, across all evaluated institutions. Institutions scoring above 100 demonstrate stronger-than-average alignment with global AI governance expectations, while scores below 100 indicate underperformance relative to the benchmarked cohort. The normalized score thus allows institutions to be directly compared based on rubric-driven policy quality, and the ranking reveals leadership differentiation in AI governance across both global and provincial systems.

Table 4.1.5
QS World Top 10 – Normalized Governance Scores Based on 50-Run Averages per Institution

Rank	Institution	Completeness	Clarity	Relevancy	Transparency	Practicality	Adjustment 1	Adjustment 2	Raw Governance Score	Normalized score	Scaled to 100 Average
1	Harvard University	8.00	7.96	10.00	6.00	8.00	2.00	3.00	44.96	50.00	121.55
2	University of Toronto	8.00	6.40	10.00	6.28	7.84	2.00	3.00	43.52	48.40	117.65
3	Carnegie Mellon University	8.00	6.00	10.00	4.24	7.40	1.42	2.44	39.50	43.93	106.79
4	University of California, Berkeley	6.00	6.00	8.92	6.00	6.00	1.98	1.96	36.86	40.99	99.65
5	University of Oxford	6.56	6.00	10.00	4.00	5.16	1.90	2.52	36.14	40.19	97.70
6	ETH Zurich	6.00	5.96	10.00	5.96	4.04	1.84	2.02	35.82	39.84	96.84
7	Massachusetts Institute of Technology	6.00	5.80	8.00	6.00	6.00	1.08	1.98	34.86	38.77	94.24

8	National University of Singapore	6.00	6.00	10.00	4.00	4.00	1.96	2.00	33.96	37.77	91.81
9	Nanyang Technological University	5.52	6.00	9.52	5.96	3.84	0.52	1.42	32.78	36.45	88.62
10	Hong Kong University of Science and Technology	6.00	5.52	8.28	3.80	5.48	0.60	1.82	31.50	35.03	85.16
	Average								**36.99**	**41.14**	**100.00**

The next section transitions from this international validation phase to the application of the same methodology across Ontario's 24 publicly funded community colleges.

4.1.6 Overview of Governance Scoring Outcomes: Ontario 24. Following the benchmarking of global leaders, the Governance (G) evaluation system was deployed across Ontario's 24 publicly funded community colleges. Governance scores for these institutions revealed substantial variability, ranging from below zero to over 40 out of a possible 50. This spread highlights significant differences in institutional readiness, policy transparency, and commitment to responsible AI integration.

A select group of colleges—such as Sheridan, Fanshawe, and Conestoga—achieved Final scores above 35, reflecting well-developed AI policy frameworks with moderate-to-high levels of transparency, clarity, and operational grounding. These institutions demonstrate a deliberate alignment with provincial and sector-wide expectations for AI governance.

The majority of colleges, however, clustered in the 20 to 35 range, indicating partial or emergent governance structures. Common issues included vague guidelines, incomplete policy coverage across stakeholder groups, and limited accessibility of AI-related documents. Several institutions scored below 10 or even landed in negative territories, often due to the following structural or procedural deficiencies:

- Absence of any dedicated AI governance or usage policy
- Policies stored in login-restricted portals, impeding public transparency
- Delegation of AI guidance to individual instructors without institutional oversight

- Minimal enforcement mechanisms or support structures for AI tool adoption

Each institution's Governance score was then mapped to a Sigma tier, following the same methodology used for the QS benchmark cohort. Institutions scoring above 35 were classified as Tier 1 (Established Governance Controls); those between 20 and 34 fell into Tier 2 (Developing Governance Structures); and institutions scoring below 20 were assigned to Tier 3 (Minimal or Absent Governance). These tiers provide a diagnostic tool for comparing institutional maturity and identifying areas for strategic improvement within Ontario's postsecondary education system.

4.1.7 Data Collection and Quality Assurance: Ontario 24. Having validated the chatbot scoring methodology through benchmarking with QS World Top 10 AI Universities, the study proceeded to apply the same deterministic evaluation framework to Ontario's 24 publicly funded community colleges. To ensure consistency and analytical rigor, the same seven-dimension rubric was uploaded to OpenAI, and evaluations were performed using an updated chatbot, which generated 50 governance evaluation reports per institution between April 21 and 22, 2025. Four Python Chatbots were deployed to perform the analysis:

- The **Rubrics Utility Bot** (see Appendix C). Same chatbot and uploaded rubrics used for QS World Top 10.
- **ON-AI-G-Build-204J-FullSafe** (see Appendix J) a modified version of Bench-Build-180F used for World Top 10**,** conducted web scraping of institutional AI policy documents across Ontario's 24 colleges. Natural Language Processing (NLP) routines extracted structured text snippets, which were then evaluated using the preloaded rubric. All evaluations produced fully explainable outputs and rubric-justified scores. The modifications were introduced to navigate unique web designs and hidden PDF policy documents of several colleges.
- The **Six-Sigma-Parser-1– Analytic Stability Testing Bot** (see Appendix E). Same chatbot used for QS World Top 10 through Gage Repeatability and Reproducibility (R&R) testing.

- The **Six-Sigma-Monte-Carlo-4 – Predictive Modeling Bot** (see Appendix F), Same chatbot used for QS World Top 10 to model one million virtual evaluations per university by applying controlled ±7-point tolerance across rubric attributes.

This approach yielded both mean scores and augmented Sigma tiers for each Ontario college, enabling reproducibility-certified comparisons with global institutions. The following section presents those results, including mode scores, sigma classifications, and interpretive commentary on provincial governance maturity in the context of generative AI adoption.

Table 4.4.7A presents the Repeatability and Reproducibility (R&R) results for AI Governance policy evaluations conducted across Ontario's community colleges. Each institution underwent 50 deterministic chatbot scoring runs using the standardized rubric outlined in Chapter 3. The table summarizes three key metrics per institution:

- **Final Score Range:** The minimum and maximum final scores across the 50 runs.
- **Final Score Mean:** The average final score.
- **Final Score Standard Deviation:** A measure of score variability and reproducibility.

Table 4.1.7A
Ontario 24–Repeatability & Reproducibility Test Summary of 50 Runs Sorted by Standard Deviation

Institution	Final Score Range	Final Score Mean	Final Score Std. Dev
George Brown	31–33	32.86	0.4
Seneca	33–37	34.86	0.9
Loyalist	30–35	33.26	1.41
Cambrian	29–38	30.68	1.49
Fanshawe	37–43	39.52	1.84
Conestoga	30–42	36.72	1.94
Georgian	26–35	31.72	1.95
Sheridan	37–43	41.1	2.06
Durham	32–42	33.84	2.37
Algonquin	33–44	36.28	2.58
Centennial	30–37	34.94	2.7
St. Clair	16–28	25.74	3.15
Humber	30–43	35.86	3.23
Confederation	2–17	9.84	4.21

Canadore	0–30	26.32	4.42
Niagara	0–40	33.58	5.06
Overall	0-44	32.32	2.48
Excluded from Final Score Standard Deviation Calculation			
Fleming	0–0	0	0
St. Lawrence	-4–2	-3.68	1.17
Northern	-4–4	-3.76	1.25
Boreal	-4–0	-0.72	1.55
Mohawk	-4–0	-1.32	1.60
Sault	-4–2	-2.52	1.97
La Cite	-4–4	-1.32	2.20
Lambton	-4–8	3.00	3.08

Institutions are sorted by ascending standard deviation to highlight the reproducibility of the scoring process. Lower standard deviation values signal stronger consistency and reliability of the deterministic evaluation model.

Eight institutions (shaded in yellow)—Fleming, Lambton, St. Lawrence, Northern, Boreal, Mohawk, Sault, and La Cité—received such low Final Score Means that their standard deviations would be a false representation of stability. In many of these cases, the chatbot was unable to extract meaningful policy content for evaluation, aside from basic indicators such as public access. For example, Fleming College was awarded +2 solely under the Transparency category, but provided no evaluable content under the core rubric dimensions such as Completeness, Relevance, or Practicality.

To complement the deterministic consistency analysis shown in Table 4.4, a probabilistic validation was conducted using Monte Carlo simulation to project long-run evaluation stability. While Table 4.4 isolates point-in-time repeatability through standard deviation across 50 chatbot runs, Table 4.5 introduces the Defects per Million Opportunities (DPMO) metric and corresponding Sigma values. These values reflect the projected likelihood of scoring variance across one million simulated parsing events per institution, using the empirical standard deviations from the Gage R&R phase. This dual approach—anchoring deterministic results with stochastic modeling—enables the evaluation system to be stress-tested under real-world scale conditions, reinforcing both its precision and resilience.

Table 4.1.7B

Ontario 24–Monte Carlo Simulation Defects per Million for Quality Assurance (c= 1 mil) with a ±7 Aggregated Shift of ±1 for Each of the Seven Assessment Attributes sorted by Sigma value

Institution	Avg. Final	Std. Dev.	DPMO	Sigma Value	Sigma Level
George Brown	32.86	0.4	0	6.00	6σ
Seneca	34.86	0.9	0	6.00	6σ
Loyalist	33.26	1.41	0	6.00	6σ
Cambrian	30.68	1.49	3	6.00	6σ
Fanshawe	39.52	1.84	176	5.07	5σ
Conestoga	36.72	1.94	338	4.9	4σ
Georgian	31.72	1.95	346	4.89	4σ
Sheridan	41.1	2.06	663	4.71	4σ
Durham	33.84	2.37	3054	4.24	4σ
Algonquin	36.28	2.58	6626	3.98	3σ
Centennial	34.94	2.7	9333	3.85	3σ
St. Clair	25.74	3.15	26190	3.44	3σ
Humber	35.86	3.23	29833	3.38	3σ
Confederation	9.84	4.21	96272	2.8	2σ
Canadore	26.32	4.42	113425	2.71	2σ
Niagara	33.58	5.06	166229	2.47	2σ
Average	32.32	2.48	28280.50	4.40	~4σ
Fleming	0	0	0	0	0
St. Lawrence	-3.68	1.17	0	0	0
Northern	-3.76	1.25	0	0	0
Boreal	-0.72	1.55	6	0	0
Mohawk	-1.32	1.6	8	0	0
Sault	-2.52	1.97	394	0	0
La Cite	-1.32	2.2	1398	0	0
Lambton	3	3.08	23182	0	0
Distorted average with exclusion	21.66	2.19	19894.83	2.94	~3σ

Similar to the quality assurance procedures used for the QS World Top 10, Table 4..1.7A ranks institutions by standard deviation to highlight scoring consistency during the Gage R&R analysis. Table 4.1.7B presents institutions ordered by Sigma Tier, capturing the overall stability of governance scores under Monte Carlo simulation. In both cases, eight institutions were assigned a Sigma value of zero due to the absence of meaningful AI governance policy data. While technically consistent in scoring zero across all runs, including them in the reproducibility distribution would have misleadingly inflated their performance—paradoxically placing them near Six Sigma for consistently having no data.

This distinction is intentional: the Gage R&R table (Table 4.1.7A) isolates chatbot scoring precision under controlled conditions, while the Sigma Tier table (Table 4.1.7B) integrates both performance and variability, reflecting overall robustness according to Six Sigma thresholds. Together, they provide complementary views on evaluation quality—precision and durability.

To preserve the integrity of statistical benchmarking, these eight institutions were excluded from the sector-wide aggregation of score ranges, means, and standard deviations. However, their inclusion in Tables 4.1.7A and 4.1.7B has been retained for full transparency and diagnostic insight. Their scores, though normalized to zero, remain part of the institutional analysis to accurately reflect gaps in AI policy transparency, governance articulation, and public accountability.

4.1.8 Governance Ranking of Ontario 24. While the previous tables established short-term reproducibility (Table 4.1.7A) and long-term scoring stability under simulation (Table 4.1.7B), this section consolidates those insights into a comparative governance ranking. Institutions are sorted in descending order based on their average Final Governance score derived from 50 deterministic chatbot runs. This ranking reflects the relative strength and maturity of each institution's AI policy infrastructure, as publicly accessible at the time of analysis.

The assigned Sigma Tier in Table 4.1.8 reflects the statistical repeatability of each institution's score under repeated deterministic runs, measured using Six Sigma thresholds. Higher tiers denote tighter scoring distributions and stronger rubric alignment.

Table 4.1.8

Ontario 24–Governance Rankings Sorted by Mean Score and Sigma Tier

Rank	Institution	Avg. Final Governance Score	Sigma Tier
1	Sheridan	41.10	5σ
2	Fanshawe	39.52	4σ
3	Conestoga	36.72	5σ
4	Algonquin	36.28	4σ
5	Humber	35.86	3σ
6	Centennial	34.94	3σ
7	Seneca	34.86	6σ
8	Durham	33.84	4σ
9	Niagara	33.58	3σ
10	Loyalist	33.26	6σ
11	George Brown	32.86	6σ
12	Georgian	31.72	5σ
13	Cambrian	30.68	6σ
14	Canadore	26.32	3σ
15	St. Clair	25.74	3σ
16	Confederation	9.84	2σ
17	Lambton	3.00	N/A
18	Fleming	0	N/A
19	Boreal	-0.72	N/A
20	La Cite	-1.32	N/A
21	Mohawk	-1.32	N/A
22	Sault	-2.52	N/A
23	St. Lawrence	-3.68	N/A
24	Northern	-3.76	N/A

All tables in sub-sections 4.1.7 to 4.1.8 include raw data from Ontario colleges that yielded nil or insignificant information on AI governance. While these institutions are retained for transparency and diagnostic completeness, their Governance scores are assigned a value of 0 in the Transition Readiness Index (TRI), reflecting the absence of any publicly available AI policy or directive. These institutions are highlighted in yellow to distinguish them from colleges with substantive governance artifacts. Importantly, their

0 scores were excluded from the calculation of the provincial average (Governance only) used to establish the normalization baseline, in order to preserve statistical integrity and avoid distortion of the sector-wide benchmark. While they were excluded from the calculation of TRI (G), they still score in the PLAC measures.

4.1.9 Institutional-Level Reporting and Diagnostic Visualization. To enhance transparency and sector-specific engagement, the deterministic scoring model was extended to generate institution-specific reports for each of Ontario's 24 community colleges. These reports follow the same architecture as the global benchmarking appendices, but are tailored to the provincial context and institutional stakeholders. In particular, these outputs respond to the likely needs of senior academic leaders and AI governance committees seeking granular insight into their institution's standing.

Three appendices are introduced for this purpose:

- **Appendix K** – Mode-aligned report summaries and governance diagnostics for each Ontario college
- **Appendix L** – Human-readable, governance institutional summary and explanation based on mode-aligned final score.
- **Appendix M –** Monte Carlo simulation outputs, including the histogram and KDE curve visualizations used to assess scoring stability.

The Governance scores and narrative explanations presented in Appendix L were extracted from the mode-aligned report associated with each institution's most frequently occurring Final score. These reports correspond to the deterministic run timestamp identified in Appendix J as the "Best-Matched Run."

To ensure statistical robustness and scoring consistency, each of Ontario's 24 colleges was evaluated ten times across five independent batches, yielding a total of 50 reports per institution. The deterministic chatbot operated in zero-temperature mode to eliminate stochastic variability. The institutional reports in Appendix L were harvested exclusively from the first batch of evaluations, ensuring consistency of source conditions while aligning with the mode-selected final score for each college.

These additions extend the rubric framework beyond statistical benchmarking, enabling practical application and institutional self-diagnosis. Each report includes the best-matching deterministic run based on modal score alignment, as well as a full visualization of scoring variation using the same simulation parameters applied during global benchmarking.

By applying the full modeling architecture—including Gage R&R, sigma tier classification, and probabilistic histogram generation—to the Ontario dataset, the scoring system demonstrates its maturity for both macro-level benchmarking and micro-level governance diagnostics. These visual and narrative appendices may assist institutional leaders in identifying rubric-based improvement areas, planning governance policy revisions, and tracking progress in future benchmarking cycles.

4.1.10 Summary of Governance Scores as a Proxy for Institutional Will. The Governance (G) dimension of the AI Transition Readiness Index (TRI) serves as a quantitative proxy for institutional will—the strategic intent and commitment to govern AI ethically, transparently, and coherently. Governance scores in this study were derived through deterministic evaluation of publicly available artifacts, including AI policies, usage guidelines, and statements on academic integrity. Each score reflects the clarity, accessibility, and completeness of governance documentation, validated through a structured rubric and subjected to Monte Carlo simulation to assess reproducibility and scoring precision.

Among Ontario's 24 publicly funded community colleges, before adjustment, the actual average Governance score was 21.66, with wide variation in quality assurance metrics. While a few institutions—Sheridan, Fanshawe, and Conestoga—achieved scores approaching or exceeding global benchmarks, a significant number recorded zero or negative scores, indicating no publicly accessible governance infrastructure. These outcomes corresponded with lower Sigma Tiers ($\leq 3\sigma$), suggesting limited repeatability and institutional maturity in governance structures.

By contrast, institutions such as Seneca, Humber, Algonquin, and George Brown demonstrated above-average scores that may not yet be accompanied by fully structured policies but nonetheless reflect emergent governance activity. These results illustrate the diversity of institutional will across Ontario's college sector, ranging from well-articulated governance systems to near-total absence of formal oversight.

4.2 Research Question Two: Operational Capacity (Way)

This section addresses the second research question:

RQ2: To what extent do Ontario's community colleges exhibit operational capacity ("Way") to deliver AI-enabled educational outcomes?

Operational readiness was assessed using the G-PLAC model, a four-variable framework comprising Programs, Learners, Agreements, and Classification. Each attribute captures a distinct dimension of institutional capability and was scored using normalized values derived from publicly accessible datasets. Together, these scores form the Way component of the AI Transition Readiness Index (TRI), representing 50% of the composite metric.

4.2.1 Overview of G-PLAC Attributes

- **Programs (P):** Quantifies the availability and concentration of AI-focused programs offered by each college.
- **Learners (L):** Measures enrollment levels in AI-classified programs based on full-time equivalent (FTE) headcounts.
- **Agreements (A):** Evaluates alignment between each institution's Strategic Mandate Agreement (SMA) and provincial AI priorities such as digital transformation, workforce innovation, and technological adoption.
- **Classification (C):** Assesses how well institutional offerings align with federal training, immigration, and labor codes (e.g., CIP/NOC/PGWP eligibility).

Each variable was assigned equal weight (25%) in accordance with the G-PLAC design principle of analytical neutrality and mutual interdependence.

4.2.2 Data Sources and Normalization. Data were sourced from the Ontario Ministry of Colleges and Universities (MCU), institutional websites, and federal classification systems. Normalization was conducted using a midpoint benchmark: Raw values were divided by the average of the provincial minimum and maximum, then scaled to a baseline of 100. This approach avoids penalizing low performers with zeroes and enables proportionate scoring across a diverse institutional landscape.

Data for the PLAC attributes were sourced from publicly available government datasets, institutional websites, and federal classification systems. Each source was manually verified and structured for analysis. Table 4.7 summarizes the primary data sources used for each operational attribute:

Table 4.7
PLAC Attributes Data Sources

Attribute	Description	Access Method	Data Source
Programs (P)	MCU Ontario College Program Count (2023–2024)	Open Datasets–College headcount report download	college_enrolment_headcount_2023-24,xlsx
Learners (L)	Percentage of MCU Full-Time Equivalent (FTE) Enrollment by Program (2020–2025)	Open Datasets–College headcount report download	college_enrolment_headcount_2023-24,xlsx
Agreements (A)	Strategic Mandate Agreements (2020–2025)	Chatbot scraping of MCU documents	College SMAs
Classification (C)	MCU Ontario College Programs sorted by CIP (2023–2024)	Open Datasets–College headcount report download	college_enrolment_headcount_2023-24,xlsx
	IRCC Ontario Post-Graduate Work Permit Ontario Colleges	Filtered IRCC dataset	Currently PGWP eligible CIP codes
	IRCC Eligible CIP codes for science, technology, engineering and mathematics (STEM)	Filtered IRCC dataset	STEM CIP Codes

4.2.3 Sector-Wide TRI (Way) Patterns. TRI (Way) scores across Ontario's 24 publicly funded colleges revealed moderate but uneven operational readiness. Several institutions demonstrated strength in one or more operational dimensions—particularly in program breadth or learner engagement—but few achieved uniformly high performance across all four G-PLAC attributes. Notably, Seneca College and Fanshawe College scored above the provincial mean in both Programs and Agreements, suggesting a more coherent operational approach to AI integration.

Conversely, multiple colleges showed strong learner enrollment in AI-related programs but lacked supporting evidence in areas such as Strategic Mandate Agreement alignment or CIP-based classification mapping. This disparity points to an operational scenario where AI programming may be occurring in isolation, disconnected from broader policy coordination or strategic documentation.

4.2.4 Thematic Observations. Four systemic patterns emerged from the operational analysis:

- **Program Offerings Lag Behind Strategic Rhetoric:** While most colleges reference digital innovation in public statements, relatively few offer multiple or specialized AI programs classified under nationally recognized codes.
- **Learner Enrollment is Concentrated:** Enrollment in AI-related programs is disproportionately concentrated in a small number of institutions, suggesting access and scalability challenges at the system level.
- **SMAs Lack Specificity:** Strategic Mandate Agreements often invoke generic innovation language but fall short of explicitly committing to AI-specific objectives, limiting their diagnostic utility.
- **Classification Misalignment:** Some colleges offer programs tangentially related to AI (e.g., general IT or data analytics) but do not map them to federally recognized training pathways, which constrains policy funding and immigration linkage.

An additional and significant finding is the presence of colleges that scored zero on Governance (“Will”) yet demonstrated measurable AI engagement in both Programs and Learners. Institutional catalogues confirm that these colleges are actively offering AI-relevant courses despite an apparent lack of formal governance mechanisms, published policies, or ethical guidelines on AI integration. This indicates a pattern of decentralized or unsanctioned AI adoption, where individual departments or faculty members lead initiatives without institutional endorsement or oversight.

While such cases suggest local initiative and pedagogical innovation, they also raise concerns about consistency, accountability, and alignment. Without governance structures to guide ethical use, curriculum design, or staff training, these institutions may be vulnerable to reputational, operational, or equity risks, particularly as AI continues to reshape postsecondary education

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4.2.5 Implications for AI Transition Readiness. The findings suggest that operational capacity in Ontario's college system remains emergent and uneven. While several institutions are making early progress, the sector as a whole lacks structural coherence in translating strategic ambition into scalable, credentialed, and labor-aligned program delivery. The G-PLAC model reveals that without tighter coordination among program design, learner access, policy alignment, and national classification systems, the sector may struggle to move beyond experimentation toward maturity in AI education.

4.3 Research Question Three: AI Governance Comparison − Ontario vs Global Best Practices.

This section addresses the third research question:

RQ3: How does AI readiness in Ontario colleges compare to global best practices as observed in the QS World Top 10 AI universities?

This comparison is focused exclusively on the Governance (G) dimension, which is methodologically comparable across institutions. Due to contextual and structural differences, it would be inappropriate to compare the "Way" dimension (operational capacity) between community colleges and global research universities. In particular:

- Programs and Enrollment are not equivalent due to the differing missions of colleges (skills-based, applied learning) versus universities (research-intensive, theoretical)
- Strategic Mandate Agreements (SMAs) are unique to Ontario's college system and do not exist in the Top 10 AI universities.
- CIP Codes and their mapping to immigration and labor systems (e.g., PGWP eligibility) are Canada-specific and not applicable to international universities.

The quadrant analysis provides a high-level diagnostic view of each institution's strategic and operational positioning. However, understanding the broader implications of these typologies—and identifying notable outliers or cross-cutting patterns—requires a more integrative synthesis of the findings. The next section addresses this need by consolidating insights from both dimensions to inform strategic interpretation and forward-looking recommendations.

4.4 Summary of Findings

Building on the quantitative results and quadrant mapping in the previous section, this section synthesizes the empirical findings from the AI Transition Readiness Index (TRI), which evaluates both the "Will" (Governance readiness) and "Way" (Operational capacity) of Ontario's 24 publicly funded community colleges in preparing for AI integration. The analysis is structured according to the G-PLAC framework, encompassing Governance, Programs, Learners, Agreements, and Classification.

Findings are presented in alignment with the study's three research questions:

- RQ1 explores institutional Will through the Governance (G) dimension,
- RQ2 assesses institutional Way by examining operational readiness via Programs (P), Learners (L), Agreements (A), and Classification (C), and
- RQ3 benchmarks Ontario's collective AI readiness against the world's Top 10 AI universities to determine global positioning.

Each subsection provides disaggregated results, supported by tables and figures, with cumulative TRI scores recalculated as additional dimensions are integrated. This approach allows for dynamic tracking of institutional performance across both strategic and operational readiness indicators.

4.4.1 Institutional Will: Governance Readiness across Ontario Colleges. The Governance (G) dimension in the AI Transition Readiness Index (TRI) was used to evaluate institutional "Will"—that is, the strategic intent, transparency, and policy maturity of each Ontario community college in governing AI adoption. Governance scores were derived through deterministic chatbot evaluations using a structured rubric across five pillars (completeness, clarity, relevancy, transparency, and practicality), along with two adjustment dimensions. All evaluations were based exclusively on publicly accessible policy artifacts, ensuring external validity and reproducibility.

Findings revealed wide variability in governance readiness across Ontario's 24 publicly funded colleges. While institutions such as Sheridan, Fanshawe, and Conestoga scored well above the provincial average, nearly one-third of the colleges produced final governance scores of zero, reflecting the absence of discoverable AI policy documents or governance guidelines. This distribution was further validated using Gage Repeatability and Reproducibility (Gage R&R) and Monte Carlo simulation methods, confirming the reliability of the scoring process. A kernel density estimation (KDE) curve showed two distinct clusters, with a minority of colleges approaching global exemplars and a majority lagging in governance infrastructure.

The average Governance score for Ontario colleges was 21.66 out of 50. After excluding zero-scoring institutions and recalculating the mean, the adjusted average rose to 32.32, highlighting the presence of emerging governance practices in select institutions while also exposing foundational gaps across the broader sector. In comparison, the QS World Top 10 AI universities achieved a mean score of 37.08, with most scoring above 35 and exhibiting Sigma Tiers between 5σ and 6σ, indicating governance models that are both articulated and stable.

To support these findings, Table 4.4.1 summarizes the normalized Governance scores for each of Ontario's 24 colleges. The table lists rubric component scores, final raw Governance scores (out of 50), and their normalized equivalents on a benchmark scale where the adjusted provincial midpoint is set to 100**.** This normalization approach allows for fair intra-cohort comparison while still exposing absolute gaps relative to global standards.

Following the approach established for the QS World Top 10 AI Universities, the governance scores for Ontario's 24 community colleges were disaggregated into their seven underlying rubric components. These include five primary scoring pillars—Completeness, Clarity, Relevance, Transparency, and Practicality—as well as two adjustment modifiers (Adj1 and Adj2). Each institution's score reflects a 50-run deterministic average, generating a composite Final score and a corresponding normalized score benchmarked to a provincial midpoint of 100.

To ensure statistical integrity, institutions with out-of-range governance of near zero or below retained a normalized score of zero, rather than allowing such values to distort and skew the baseline calculation. The resulting rankings and scores in Table 4.4.1A form the foundation for the Governance (G) dimension within the AI Transition Readiness Index (TRI). However, the zero scores are included in computing of the composite Cumulative TRI (Scaled to 100%). The Cumulative TRI, illustrated in Table 4.4.1B, indicates the overall and progressive ranking of the composite TRI as more TRI sub-indices are included as the G-PLAC attributes accumulate.

Table 4.4.1A

Ontario 24–Normalized Governance Scores Based on Rubric Component Averages (50-Run Evaluation)

(Scores adjusted using midpoint normalization (Midpoint = 25.00), excluding institutions with low raw governance scores.)

Rank	Institution	Completeness	Clarity	Relevancy	Transparency	Practicality	Adjustment 1	Adjustment 2	Raw Governance Score	Normalized Score	Scaled to 100 Average
1	Sheridan	7.80	7.40	10.00	6.00	4.92	2.00	2.98	41.1	40.34	127.26
2	Fanshawe	8.00	6.04	10.00	6.00	5.20	1.64	2.64	39.52	38.79	122.37
3	Conestoga	6.00	6.12	8.08	7.72	5.76	1.04	1.96	36.68	36.00	113.58
4	Algonquin	7.88	6.28	8.36	6.24	4.16	1.30	1.94	36.16	35.49	111.97
5	Humber	7.00	6.04	8.88	6.00	4.96	0.98	2.00	35.86	35.20	111.04
6	Centennial	6.00	6.00	8.04	7.40	5.16	0.60	1.72	34.92	34.28	108.13
7	Seneca	6.00	7.72	8.12	6.00	4.00	1.02	2.00	34.86	34.22	107.94
8	Durham	6.44	6.04	8.16	6.04	4.20	1.06	1.86	33.8	33.18	104.66
9	Niagara	5.88	6.24	7.84	5.96	3.96	1.72	1.94	33.54	32.92	103.86
10	Loyalist	6.00	6.00	8.08	6.48	4.00	0.80	1.90	33.26	32.65	102.99
11	George Brown	6.00	6.00	8.00	6.00	3.96	1.00	1.88	32.84	32.23	101.69
12	Georgian	6.00	5.52	10.00	5.32	2.12	0.84	1.92	31.72	31.13	98.22
13	Cambrian	6.04	4.12	8.00	6.00	3.36	1.04	2.00	30.56	30.00	94.63
14	Canadore	5.88	3.88	8.04	5.60	3.64	-1.88	1.16	26.32	25.83	81.50
15	St. Clair	4.00	5.92	7.52	5.96	2.00	0.06	0.28	25.74	25.27	79.70
16	Confederation	3.24	2.00	4.44	4.76	1.16	-2.92	-2.84	9.84	9.66	30.47
17	Lambton	1.96	1.08	1.24	3.88	0.84	-3.00	-3.00	3	0.00	0.00
18	Fleming	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0.00	0.00

19	Boreal	0.72	0.00	0.00	1.96	0.00	-1.62	-1.62	0	0.00	0.00
20	Mohawk	0.44	0.00	0.00	1.00	0.00	-1.38	-1.38	0	0.00	0.00
21	La Cite	0.16	0.04	0.00	0.96	0.04	-1.32	-1.32	0	0.00	0.00
22	Sault	0.28	0.04	0.00	1.60	0.00	-2.28	-2.28	0	0.00	0.00
23	St. Lawrence	0.08	0.04	0.00	2.16	0.00	-2.94	-2.94	0	0.00	0.00
24	Northern	0.04	0.04	0.00	2.00	0.04	-2.94	-2.94	0	0.00	0.00

Table 4.4.1B
TRI Accumulation Table (Governance Only) Sorted by Cumulative TRI

Institution	TRI (G) 50%	TRI (P) 12.5%	TRI (L) 12.5%	TRI (A) 12.5%	TRI (C) 12.5%	Cumulative TRI Scaled to 100%
Sheridan	63.63					63.63
Fanshawe	61.19					61.19
Conestoga	56.79					56.79
Algonquin	55.98					55.98
Humber	55.52					55.52
Centennial	54.06					54.06
Seneca	53.97					53.97
Durham	52.33					52.33
Niagara	51.93					51.93
Loyalist	51.49					51.49
George Brown	50.84					50.84
Georgian	49.11					49.11
Cambrian	47.31					47.31
Canadore	40.75					40.75
St. Clair	39.85					39.85
Confederation	15.23					15.23
Boreal	0					0.00
Fleming	0					0.00
La Cite	0					0.00
Lambton	0					0.00
Mohawk	0					0.00
Northern	0					0.00
Sault	0					0.00
St. Lawrence	0					0.00

4.4.2. Institutional Way: Operational Capacity and PLAC Scores. Operational Capacity ("Way"). The four PLAC attributes formulate the results of RQ2, which are collected through data mining of open government datasets (Programs, Learners, and Classifications) and deterministic chatbot-based assessments of Strategic Mandate Agreements (Agreements).

To evaluate the Programs (P), Learners (L) and Classification (C) dimensions of institutional operational capacity, the study employed R-based data mining on open-access datasets published by the Ontario Ministry of Colleges and Universities.

Specifically, the analysis ingested the 2023–2024 College Enrolment Headcount Excel file and cross-referenced program titles and codes against a validated list of 39 CIP codes (see Appendix N) related to AI-relevant fields, including computer science, data analytics, robotics, and automation.

Two custom scripts were developed and executed within two R Markdown (.Rmd) files to clean, process, and normalize enrollment data. Outputs included cross-institutional comparisons of AI program volume and full-time equivalent (FTE) learner participation. These results were visualized using bar charts and tabulated summaries to assess sector-wide trends and institutional concentration.

To ensure transparency and reproducibility, the following files are appended:

G-PLAC Attributes (P) and (L)

- Appendix O: GPLANET_P_L_Capstone.R (R script)
- Appendix P: GPLANET_P_L_Capstone.Rmd (R Markdown file)
- Appendix Q: GPLANET_P_L_Capstone.pdf (Summary output and plots)

G-PLAC Attribute (A)

- Appendix R: SMA_Scorer_LLM_v4.py (Python Chatbot script)
- Appendix S: SAM URLs.xlsx (Source SMAs)
- Appendix T: SMA_College_Summaries.txt (Summary output)

G-PLAC Attribute (C)

- Appendix U: CIP_parser.R (R script)
- Appendix V: AI CIP Variety Analysis-1.Rmd (R Markdown file)
- Appendix W: AI CIP Variety Analysis-1.pdf (Summary output and plots)

These materials support verification of results and serve as a transferable toolkit for future benchmarking efforts.

G-PLAC Attribute (P) – Program Count. The Programs Count captures each college's curricular commitment to AI by measuring the number of approved academic programs aligned with AI-related fields. This indicator reflects how extensively an institution has embedded AI content within its formal offerings, signaling readiness to equip learners for algorithmically mediated workplaces.

The underlying taxonomy is based on the AI-Relevant CIP framework developed in the Capstone project, which identified 39 standardized CIP codes associated with artificial intelligence, robotics, machine learning, data science, and cybersecurity. These codes were applied to the 2023–2024 dataset of approved programs published by the Ontario Ministry of Colleges and Universities. A custom R script processed these data, yielding both the total number of AI programs and their proportion relative to overall offerings.

Figure 4.4.2(P)
AI Vs. Total Programs By College (2023–2024)

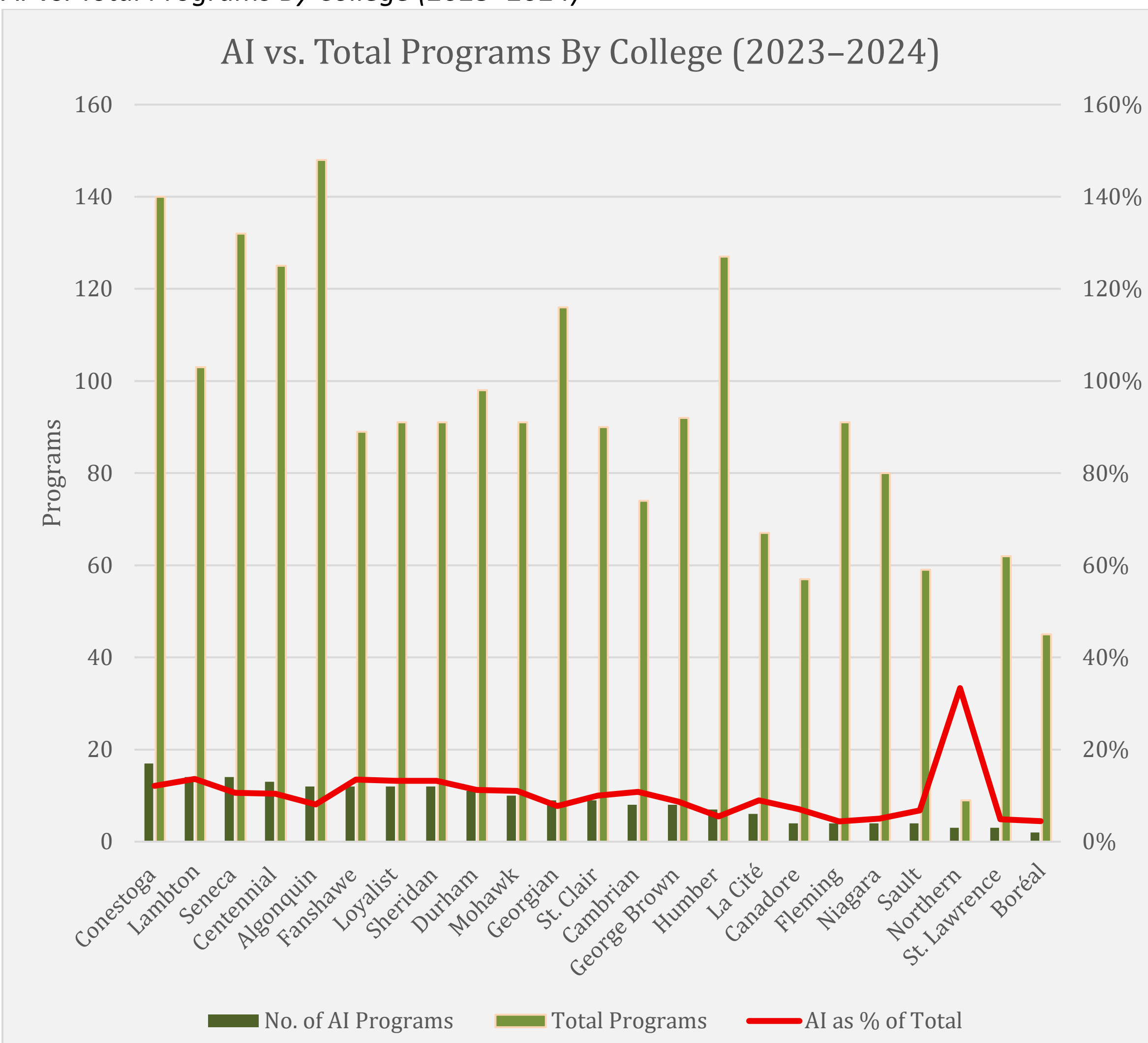


Figure 4.4.2A illustrated that almost all the institutions' percentage of AI programs offering falls in line within the provincial range of almost 14 to 4, except for

Northern College which sees a spike to 33%. The spike shows Northern has one-third of its overall programs are AI-related, although the actual number of offerings remain low at 3.

Table 4.4.2(P)A
AI Programs sorted by TRI (P) Sub-Index (2023–2024)

College	AI Programs	Total Programs	AI as % of Total	Normalized TRI (P)	Adjusted to 100
Conestoga	17	140	12.14	178.95	204.00
Lambton	14	103	13.59	147.37	168.00
Seneca	14	132	10.61	147.37	168.00
Centennial	13	125	10.40	136.84	156.00
Algonquin	12	148	8.11	126.32	144.00
Fanshawe	12	89	13.48	126.32	144.00
Loyalist	12	91	13.19	126.32	144.00
Sheridan	12	91	13.19	126.32	144.00
Durham	11	98	11.22	115.79	132.00
Mohawk	10	91	10.99	105.26	120.00
Georgian	9	116	7.76	94.74	108.00
St. Clair	9	90	10.00	94.74	108.00
Cambrian	8	74	10.81	84.21	96.00
George Brown	8	92	8.70	84.21	96.00
Humber	7	127	5.51	73.68	84.00
La Cité	6	67	8.96	63.16	72.00
Canadore	4	57	7.02	42.11	48.00
Fleming	4	91	4.40	42.11	48.00
Niagara	4	80	5.00	42.11	48.00
Sault	4	59	6.78	42.11	48.00
Northern	3	9	33.33	31.58	36.00
St. Lawrence	3	62	4.84	31.58	36.00
Boréal	2	45	4.44	21.05	24.00
Confederation	2	51	3.92	21.05	24.00

For G-PLAC scoring purposes, the normalized “P” score is derived from the raw count of AI-aligned programs at each institution, scaled using midpoint normalization.

This avoids the distortions caused by percentage metrics, which tend to inflate scores at institutions with small program catalogs (e.g., Northern). Percentage values remain useful for descriptive comparison and are presented below as a contextual metric. This supply-side indicator complements learner enrollment data shown in Figure 4.4.2(P)B,

Table 4.4.2(P)B
Cumulative TRI (Governance and Programs)

Institution	TRI (G) 50%	TRI (P) 12.5%	TRI (L) 12.5%	TRI (A) 12.5%	TRI (C) 12.5%	Cumulative TRI Scaled to 100%
Conestoga	56.79	25.5				82.29
Sheridan	63.63	18				81.63
Fanshawe	61.19	18				79.19
Seneca	53.97	21				74.97
Algonquin	55.98	18				73.98
Centennial	54.06	19.5				73.56
Loyalist	51.49	18				69.49
Durham	52.33	16.5				68.83
Humber	55.52	10.5				66.02
George Brown	50.84	12				62.84
Georgian	49.11	13.5				62.61
Cambrian	47.31	12				59.31
Niagara	51.93	6				57.93
St. Clair	39.85	13.5				53.35
Canadore	40.75	6				46.75
Lambton	0	21				21.00
Confederation	15.23	3				18.23
Mohawk	0	15				15.00
La Cite	0	9				9.00
Fleming	0	6				6.00
Sault	0	6				6.00
Northern	0	4.5				4.50
St. Lawrence	0	4.5				4.50
Boreal	0	3				3.00

Together, the Programs and Learners dimensions highlight both opportunity and fragmentation in institutional AI readiness. While some colleges demonstrate programmatic leadership and high student engagement in AI-related fields, others remain at the initial stages of integration. These disparities substantiate the need for a composite, cross-validated metric like the AI Transition Readiness Index (TRI) to guide sector-wide policy alignment and capacity planning.

As more attributes are added to calculate the cumulative TRI, we will observe shifts in institutional standings. This study will re-rank the TRI results dynamically as additional components—such as Agreements and Classification—are introduced. This evolving index reflects the holistic nature of readiness: an institution that leads in governance may fall in the rankings if its operational dimensions fail to deliver proportionate outcomes. Conversely, colleges with modest governance scores may rise due to strong curricular or learner engagement. The TRI model thus enables a fair and evolving assessment of AI readiness over time.

G-PLAC Attribute (L) −AI Learner Percentage. The Learner (L) dimension captures the proportion of full-time equivalent (FTE) students enrolled in AI-designated programs as a share of total institutional enrollment. This indicator provides insight into how effectively colleges are channeling students into AI-focused fields and reflects broader institutional capacity-building and curriculum alignment in the context of the Fourth Industrial Revolution.

Enrollment patterns reveal notable disparities in institutional uptake of AI program delivery. Georgian College led all institutions, with approximately 21% of its student population engaged in AI-related programs. Sheridan, Mohawk, and Seneca followed closely, each reporting AI learner ratios between 17–19%. These institutions not only demonstrate curriculum investment but also growing student demand for AI-skills pathways.

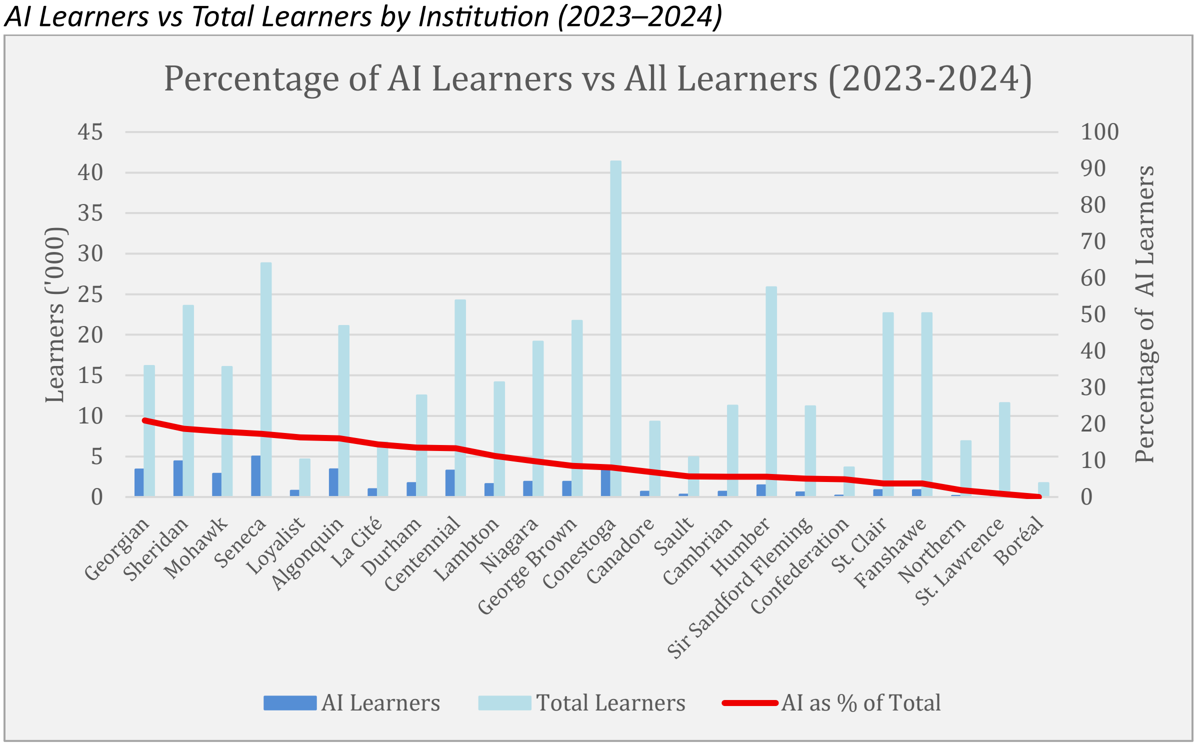
In contrast, institutions such as Boréal, St. Lawrence, and Northern reported AI enrollment levels below 2%, indicating limited exposure to algorithmic or digital skills training within their current program mix. This disparity signals uneven institutional engagement with AI capacity-building, raising important questions about equitable access to automation-era competencies across the province.

To enable fair comparison across colleges of varying size, the Learner (L) score is expressed as a percentage of total enrollment, not a raw FTE count. While absolute enrollment numbers may reflect program scale, they also correlate heavily with institutional size. Using a normalized ratio ensures that smaller institutions demonstrating strong relative AI uptake (e.g., Loyalist or La Cité) are not structurally penalized in the G-PLAC index. This normalization approach aligns with international benchmarking principles and allows the L metric to serve as a comparative signal of proportional AI engagement rather than capacity alone.

The provincial average for AI enrollment hovered between 9% and 10%, based on a manually downloaded, government-published FTE dataset processed using custom R scripts (see Capstone Appendix). Variations in data reporting consistency—especially among colleges with minimal or no AI enrollment—necessitated normalization to ensure valid inter-institutional comparison.

Figure 4.4.2(L) presents the learner distribution graphically, while Table 4.14 provides a detailed account of both raw enrollment counts and normalized percentages for each institution.

Figure 4.4.2(L)
AI Learners vs Total Learners by Institution (2023–2024)



This figure illustrates the proportion of full-time equivalent (FTE) students enrolled in AI-designated programs at each of Ontario's 24 public community colleges. Institutions such as Georgian, Sheridan, Mohawk, Seneca, Loyalist and Algonquin show the highest levels of AI learner engagement, each exceeding 15% of total enrollment. In contrast, several colleges report fewer than 2% of learners in AI-related fields.

Table 4.4.2(L)A
AI Enrollment as a Percentage of Total Enrollment by Colleges (2023–2024)

College	AI Learners	Total Learners	AI as % of Total	Normalized TRI (L)	Adjusted to 100
Georgian	3388	16,154	20.97	200.00	218.64
Sheridan	4409	23,567	18.71	178.45	195.07
Mohawk	2869	16,049	17.88	170.53	186.42
Seneca	4987	28,801	17.32	165.19	180.58
Loyalist	757	4,641	16.31	155.56	170.05
Algonquin	3,395	21,101	16.09	153.46	167.76
La Cité	972	6,740	14.42	137.53	150.35
Durham	1,694	12,528	13.52	128.95	140.96
Centennial	3,245	24,222	13.4	127.80	139.71
Lambton	1,589	14,153	11.23	107.11	117.09
Niagara	1,885	19,151	9.84	93.85	102.59
George Brown	1,862	21,707	8.58	81.83	89.46
Conestoga	3367	41,374	8.14	77.63	84.87
Canadore	641	9,299	6.89	65.71	71.84
Sault	277	4,920	5.63	53.70	58.70
Cambrian	632	11,278	5.6	53.41	58.39
Humber	1444	25,846	5.59	53.31	58.28
Fleming	557	11,167	4.99	47.59	52.03
Confederation	175	3,626	4.83	46.07	50.36
St. Clair	844	22,680	3.72	35.48	38.79
Fanshawe	844	22,680	3.72	35.48	38.79
Northern	129	6,876	1.88	17.93	19.60
St. Lawrence	107	11,563	0.93	8.87	9.70
Boréal	0	1,705	0	0.00	0.00

Together with the Programs (P) indicator, the Learners (L) dimension confirms a pattern of opportunity and fragmentation. While some colleges show strong student uptake in AI fields, others remain at an early stage of readiness. These findings reinforce the necessity of a composite metric—such as the AI Transition Readiness Index (TRI)—to support evidence-informed policy alignment and system-wide capacity planning.

Table 4.4.2(L)B
Cumulative TRI (Governance, Programs, and Learners)

Institution	TRI (G) 50%	TRI (P) 12.5%	TRI (L) 12.5%	TRI (A) 12.5%	TRI (C) 12.5%	Cumulative TRI Scaled to 100%
Seneca	53.97	21	24.38			99.36
Algonquin	55.98	18	20.97			94.95
Conestoga	56.79	25.5	10.61			92.90
Loyalist	51.49	18	23.30			92.80
Centennial	54.06	19.5	17.46			91.03
George Brown	50.84	12	27.33			90.17
Sheridan	63.63	18	6.50			88.14
Durham	52.33	16.5	17.62			86.45
Humber	55.52	10.5	18.79			84.81
Fanshawe	61.19	18	4.85			84.03
Georgian	49.11	13.5	7.29			69.90
Cambrian	47.31	12	7.30			66.61
Niagara	51.93	6	2.45			60.38
St. Clair	39.85	13.5	4.85			58.20
Canadore	40.75	6	8.98			55.73
Lambton	0	21	21.26			42.26
Sault	0	6	22.57			28.57
Mohawk	0	15	12.82			27.82
Confederation	15.23	3	6.29			24.53
La Cite	0	9	14.64			23.64
Fleming	0	6	11.18			17.18
Northern	0	4.5	7.34			11.84
St. Lawrence	0	4.5	1.21			5.71
Boreal	0	3	0.00			3.00

G-PLAC Attribute (A) – Strategic Mandate Agreements. The "Agreement" (A) attribute within the G-PLAC framework assesses how well each Ontario college's Strategic Mandate Agreement (SMA) aligns with institutional readiness for Artificial Intelligence (AI). Specifically, it examines AI alignment across five dimensions: Strategic AI Commitment, AI-Related Programming, Applied Research in AI, Community/Industry Partnerships, and Workforce Alignment. Evaluation was conducted using a deterministic

GPT-4-Turbo model (temperature = 0.0) that applied a structured rubric scoring each dimension from 0 to 10. The rubric was explicitly defined in the prompt, ensuring full reproducibility and grounded interpretation.

Across all 24 colleges, SMA alignment with AI readiness was found to be generally low to moderate. The highest raw rubric score observed was 30 out of 50 (Lambton), while the lowest was 8 out of 50 (several institutions including Confederation, Fanshawe, St. Clair and St. Lawrence). No institution received a perfect score in any dimension, and many institutions scored below 4 in critical areas such as Strategic AI Commitment and Applied Research in AI.

To better visualize the range and distribution of AI alignment across Ontario's 24 colleges, Figure 4.4.2 A) presents a heatmap of rubric scores by dimension, while Table 4.4.2(A) details the raw scores for all five dimensions across institutions.

Figure 4.4.2(A)

Heatmap of AI Alignment Scores by College and Agreement Dimensions

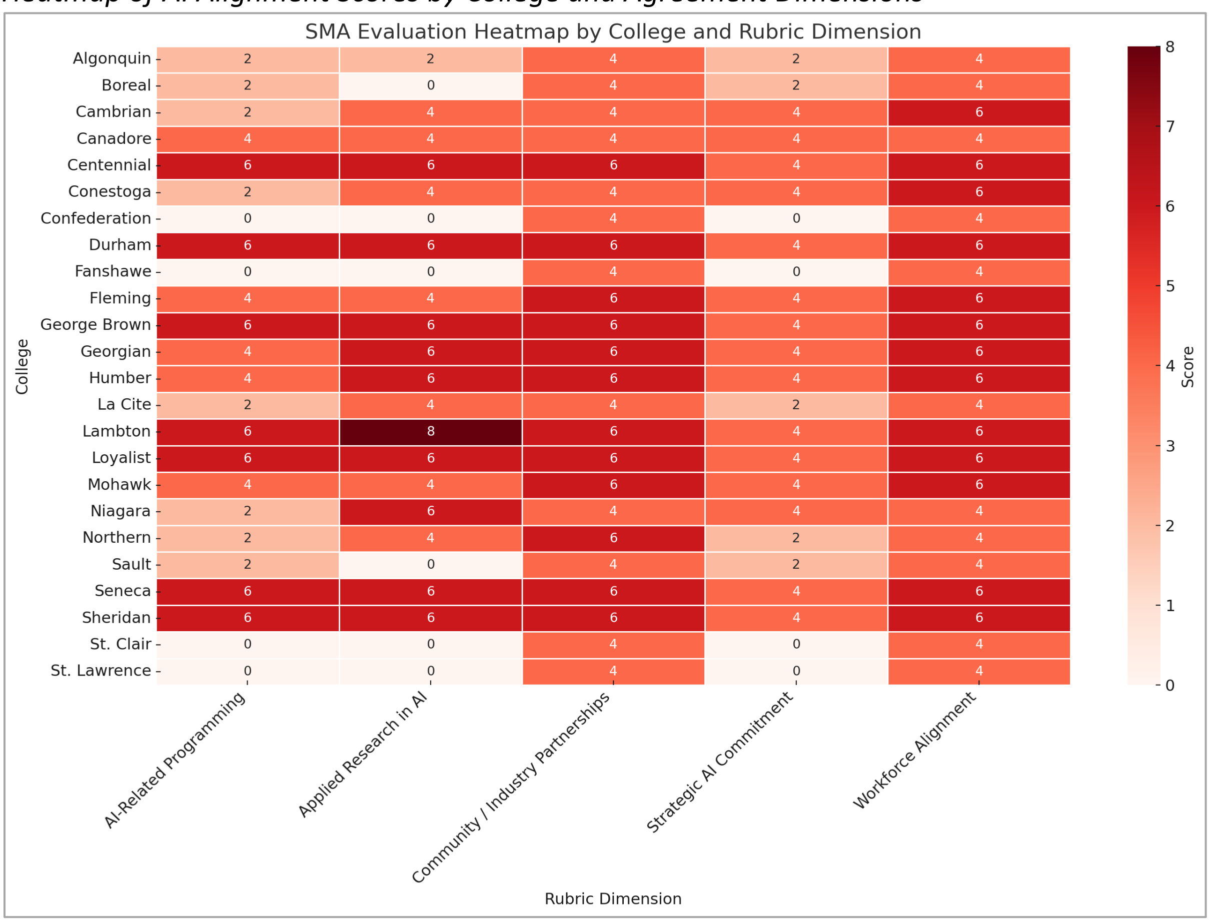


Figure 4.4.2(A) visually depicts the rubric-based AI alignment scores across Ontario's 24 colleges. Institutions are listed along the vertical axis, while the five rubric dimensions appear on the horizontal axis. Darker red tones indicate stronger alignment with AI readiness in a given dimension, while lighter tones reflect weaker performance. The visual format highlights not only inter-institutional differences but also which dimensions (e.g., AI-Related Programming, Strategic AI Commitment) show systemic strengths or gaps across the sector. This allows for quick identification of both high-performing colleges and sector-wide challenges in AI integration**.**

Notably, Fleming College demonstrated stronger-than-average alignment with AI goals, scoring well in AI-Related Programming and Community/Industry Partnerships. Centennial, Durham, Humber, Loyalist, and Sheridan also presented moderately developed SMA strategies, showing emerging efforts in programming and external collaboration, but often lacking in strategic articulation or workforce considerations.

Conversely, colleges such as Algonquin, Boreal, St. Clair, and Northern reflected minimal AI emphasis in their agreements, with low scores across most or all rubric dimensions. These institutions show little evidence of structured commitments to AI, suggesting their SMAs were more traditionally focused or generic in vision.

While many colleges performed modestly in one or two dimensions, the most consistently weak dimension across the board was Strategic AI Commitment. This dimension assesses whether AI is positioned as an institutional priority—strategically and operationally. Its weakness suggests that while some colleges may be experimenting with programs or partnerships, few have yet positioned AI as a foundational element of their institutional strategy.

To further illustrate the specific rubric outcomes underlying the heatmap visualization, Table 4.4.2(A) presents the raw scores assigned to each institution across the five AI alignment dimensions evaluated within their Strategic Mandate Agreements. These include: AI-Related Programming, Applied Research in AI, Community/Industry Partnerships, Strategic AI Commitment, and Workforce Alignment. The table also includes each institution's total raw score out of 50, its normalized TRI (A) score relative to the provincial average, and the final adjusted TRI (A) value scaled to a base of 100 for cross-institutional comparison. This breakdown provides greater granularity into institutional strengths and gaps, reinforcing the narrative of uneven yet emerging alignment with AI readiness across Ontario's college sector.

Table 4.4.2(A)
Rubric Scores for SMA Alignment with AI Readiness (By Institution)

Institution	AI-Related Programming	Applied Research in AI	Community / Industry Partnerships	Strategic AI Commitment	Workforce Alignment	Raw TRI (A)	Normalized TRI	Adjusted TRI (A)
Lambton	6	8	6	4	6	30	157.89	149.38
Centennial	6	6	6	4	6	28	147.37	139.42
Durham	6	6	6	4	6	28	147.37	139.42
George Brown	6	6	6	4	6	28	147.37	139.42
Loyalist	6	6	6	4	6	28	147.37	139.42
Seneca	6	6	6	4	6	28	147.37	139.42
Sheridan	6	6	6	4	6	28	147.37	139.42
Georgian	4	6	6	4	6	26	136.84	129.46
Humber	4	6	6	4	6	26	136.84	129.46
Fleming	4	4	6	4	6	24	126.32	119.50
Mohawk	4	4	6	4	6	24	126.32	119.50
Cambrian	2	4	4	4	6	20	105.26	99.59
Canadore	4	4	4	4	4	20	105.26	99.59
Conestoga	2	4	4	4	6	20	105.26	99.59
Niagara	2	6	4	4	4	20	105.26	99.59
Northern	2	4	6	2	4	18	94.74	89.63
La Cite	2	4	4	2	4	16	84.21	79.67
Algonquin	2	2	4	2	4	14	73.68	69.71
Boreal	2	0	4	2	4	12	63.16	59.75
Sault	2	0	4	2	4	12	63.16	59.75
Confederation	0	0	4	0	4	8	42.11	39.83
Fanshawe	0	0	4	0	4	8	42.11	39.83
St. Clair	0	0	4	0	4	8	42.11	39.83
St. Lawrence	0	0	4	0	4	8	42.11	39.83

These relatively low-to-moderate raw alignment levels must be interpreted in their historical context. Most SMAs were finalized in 2020—prior to the global diffusion of Generative AI technologies. The public release of ChatGPT (OpenAI) and Gemini (Google) in late 2022 and Microsoft Bing Chat (Predecessor of Copilot) in late 2023 marked a watershed moment for AI adoption and awareness. As such, the existing SMAs are more reflective of pre-Generative AI thinking and priorities. It will be particularly insightful to observe the next round of SMA negotiations, expected in 2026, to see whether colleges exhibit a sharper and more strategic pivot toward AI readiness. Shifts in the “A” scores may serve as a bellwether of institutional transition into the AI era. For detailed institution-by-institution summaries, see Appendix T.

Table 4.4.2(A)B

Cumulative TRI (Governance, Programs, Learners and Assignments)

Institution	TRI (G) 50%	TRI (P) 12.5%	TRI (L) 12.5%	TRI (A) 12.5%	TRI (C) 12.5%	Cumulative TRI Scaled to 100%
Seneca	53.97	21	24.38	2.88		102.24
Algonquin	55.98	18	20.97	2.48		97.43
Loyalist	51.49	18	23.30	2.76		95.55
Conestoga	56.79	25.5	10.61	1.25		94.15
George Brown	50.84	12	27.33	3.23		93.40
Centennial	54.06	19.5	17.46	2.07		93.09
Sheridan	63.63	18	6.50	0.77		88.90
Durham	52.33	16.5	17.62	2.08		88.53
Humber	55.52	10.5	18.79	2.22		87.04
Fanshawe	61.19	18	4.85	0.57		84.61
Georgian	49.11	13.5	7.29	0.86		70.76
Cambrian	47.31	12	7.30	0.86		67.48
Niagara	51.93	6	2.45	0.29		60.67
St. Clair	39.85	13.5	4.85	0.57		58.77
Canadore	40.75	6	8.98	1.06		56.79
Lambton	0	21	21.26	2.51		44.77
Sault	0	6	22.57	2.67		31.24
Mohawk	0	15	12.82	1.52		29.34
La Cite	0	9	14.64	1.73		25.37
Confederation	15.23	3	6.29	0.74		25.27
Fleming	0	6	11.18	1.32		18.50

Northern	0	4.5	7.34	0.87		12.71
St. Lawrence	0	4.5	1.21	0.14		5.86
Boreal	0	3	0.00	0.00		3.00

G-PLAC Attribute (C) – CIP-to-Market Alignment. To determine which programs across Ontario's 24 public colleges contain AI-relevant components, this study employed a content-based filter using the Government of Canada's Classification of Instructional Programs (CIP) taxonomy. A curated list of 39 CIP codes was identified to capture disciplines either explicitly focused on Artificial Intelligence (e.g., 11.0102 Artificial Intelligence, 15.0405 Robotics Technology) or inclusive of adjacent competencies such as data science, programming, informatics, automation, simulation, and machine learning infrastructure. This includes codes from traditional computing domains (e.g., 11.0701 Computer Science), technical streams (e.g., 15.1202 Computer Systems Technology), and emerging interdisciplinary areas (e.g., 51.2706 Medical Informatics, 30.1601 Accounting and Computer Science).

By analyzing course offering reports provided by the Ontario government against this CIP-based taxonomy, the study quantified both the absolute number and the percentage of AI-relevant programs offered per institution. However, the "C" dimension specifically focuses on the variety of CIP codes covered, rather than total program volume. This approach emphasizes how broadly each institution's curriculum spans the AI- and automation-related domain space, thereby offering a proxy for institutional versatility in meeting evolving technological skill demands.

In this model, a college offering programs aligned with a wide array of the 39 identified CIP codes demonstrates a more diversified AI curriculum portfolio, capable of supporting learners across multiple AI-relevant career pathways. Institutions with limited CIP coverage, by contrast, may signal either a narrow specialization or a lag in adapting to emerging workforce requirements.

This variety-based approach is particularly significant in the context of Ontario's job market, where artificial intelligence is disrupting not only core technical roles but also fields such as health, finance, transportation, and media. The "C" score therefore functions as a curricular breadth indicator, capturing how extensively each college aligns its offerings with the interdisciplinary and rapidly evolving nature of AI employment demands.

The CIP data was mined using a custom R script (see Appendix N), which filtered the 2023–2024 program inventory based on the curated CIP-39 list. The resulting output generated a table ranking all 24 Ontario colleges by the number of distinct AI-related CIP codes offered. A bar plot was also produced to help readers visualize each institution's CIP variety coverage, with percentage labels indicating each college's relative breadth of AI program alignment. The final "C" score was normalized as a percentage of total possible coverage (i.e., 39 codes), enabling consistent scoring within the G-PLAC framework and comparability across institutions of different sizes or program volumes.

Figure 4.4.2(C)
AI-Relevant CIP Variety by College (2023–2024)

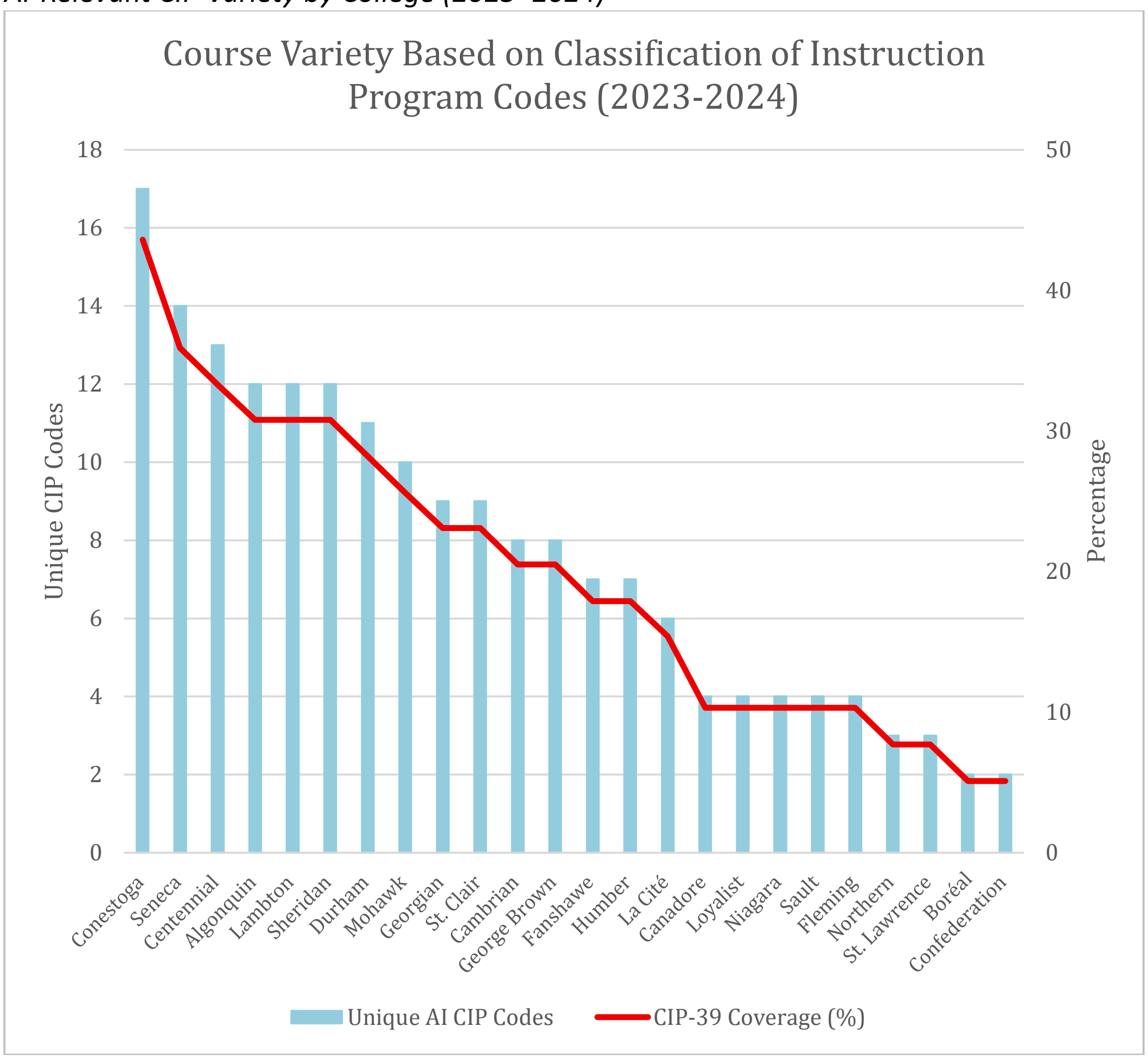


Figure 4.4.2(C) presents the number of unique AI-relevant CIP codes (from the CIP-39 taxonomy) offered by each of Ontario's 24 public colleges, based on 2023–2024 program data. Colleges are ranked by CIP variety, with percentage labels indicating their coverage of the 39-category benchmark. This chart supports analysis of the "C" dimension in the G-PLAC framework, where CIP diversity reflects curricular alignment with AI-related workforce demands.

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Table 4.4.2(C)A
Summary of AI-Relevant CIP Coverage Across Ontario Colleges

Institution	Unique AI CIP Codes	CIP-39 Coverage (%)	Normalized TRI (C)	TRI (C)Adjusted to 100
Conestoga	17	43.6	44.74	220.54
Seneca	14	35.9	36.84	181.62
Centennial	13	33.3	34.21	168.65
Algonquin	12	30.8	31.58	155.68
Lambton	12	30.8	31.58	155.68
Sheridan	12	30.8	31.58	155.68
Durham	11	28.2	28.95	142.70
Mohawk	10	25.6	26.32	129.73
Georgian	9	23.1	23.68	116.76
St. Clair	9	23.1	23.68	116.76
Cambrian	8	20.5	21.05	103.78
George Brown	8	20.5	21.05	103.78
Fanshawe	7	17.9	18.42	90.81
Humber	7	17.9	18.42	90.81
La Cité	6	15.4	15.79	77.84
Canadore	4	10.3	10.53	51.89
Loyalist	4	10.3	10.53	51.89
Niagara	4	10.3	10.53	51.89
Sault	4	10.3	10.53	51.89
Fleming	4	10.3	10.53	51.89
Northern	3	7.7	7.89	38.92
St. Lawrence	3	7.7	7.89	38.92
Boréal	2	5.1	5.26	25.95
Confederation	2	5.1	5.26	25.95

Table 4.4.2(C)A lists the number, percentage of distinct AI-relevant CIP codes, mid-point normalized TRI (C) and adjusted-to-100 sub-index represented in each institution's program portfolio, based on the curated CIP-39 list.

Table 4.4.2(C)B
Cumulative TRI (Governance, Programs, Learners, Assignments and Classification)

Institution	TRI (G) 50%	TRI (P) 12.5%	TRI (L) 12.5%	TRI (A) 12.5%	TRI (C) 12.5%	Cumulative TRI Scaled to 100%
Seneca	53.97	21	24.38	2.88	2.84	105.08
Algonquin	55.98	18	20.97	2.48	2.43	99.87
Conestoga	56.79	25.5	10.61	1.25	3.45	97.60
Loyalist	51.49	18	23.30	2.76	0.81	96.36
Centennial	54.06	19.5	17.46	2.07	2.64	95.73
George Brown	50.84	12	27.33	3.23	1.62	95.03
Sheridan	63.63	18	6.50	0.77	2.43	91.34
Durham	52.33	16.5	17.62	2.08	2.23	90.76
Humber	55.52	10.5	18.79	2.22	1.42	88.45
Fanshawe	61.19	18	4.85	0.57	1.42	86.03
Georgian	49.11	13.5	7.29	0.86	1.82	72.58
Cambrian	47.31	12	7.30	0.86	1.62	69.10
Niagara	51.93	6	2.45	0.29	0.81	61.48
St. Clair	39.85	13.5	4.85	0.57	1.82	60.60
Canadore	40.75	6	8.98	1.06	0.81	57.60
Lambton	0	21	21.26	2.51	2.43	47.20
Sault	0	6	22.57	2.67	0.81	32.05
Mohawk	0	15	12.82	1.52	2.03	31.37
La Cite	0	9	14.64	1.73	1.22	26.58
Confederation	15.23	3	6.29	0.74	0.41	25.68
Fleming	0	6	11.18	1.32	0.81	19.32
Northern	0	4.5	7.34	0.87	0.61	13.31
St. Lawrence	0	4.5	1.21	0.14	0.61	6.46
Boreal	0	3	0.00	0.00	0.41	3.41

4.5 Summary of Cumulative Findings

The cumulative Transition Readiness Index (TRI) results presented in this chapter provide a robust, stage-by-stage synthesis of institutional readiness across Ontario's 24 public community colleges. Anchored in the G-PLAC framework—comprising

Governance (G), Programs (P), Learners (L), Strategic Agreements (A), and Classification (C)—the TRI was methodically constructed using appropriate proportional weights: Governance at 50% and each of the four PLAC attributes at 12.5%.

This final composite scoring model corrected earlier misalignments and applied consistent scaling logic to each subcomponent. The resulting Ranked Normalized TRI table (Table 4.5) offers a statistically sound, apples-to-apples comparison across institutions, with all values normalized to a 100-point scale. The integrity of the framework was preserved by distributing evaluative weight according to the intended influence of each variable.

Table 4.5
Ranked TRI based on Normalized Governance and PLAC Scores

Ranking	Institution	TRI (G) 50%	TRI (PLAC) 50%	Aggregated Sub-total
1	Seneca	53.97	51.11	105.08
2	Algonquin	55.98	43.88	99.87
3	Conestoga	56.79	40.81	97.60
4	Loyalist	51.49	44.87	96.36
5	Centennial	54.06	41.66	95.73
6	George Brown	50.84	44.18	95.03
7	Sheridan	63.63	27.70	91.34
8	Durham	52.33	38.43	90.76
9	Humber	55.52	32.93	88.45
10	Fanshawe	61.19	24.84	86.03
11	Georgian	49.11	23.47	72.58
12	Cambrian	47.31	21.78	69.10
13	Niagara	51.93	9.55	61.48
14	St. Clair	39.85	20.75	60.60
15	Canadore	40.75	16.85	57.60
16	Lambton	0.00	47.20	47.20
17	Sault	0	32.05	32.05
18	Mohawk	0	31.37	31.37
19	La Cite	0	26.58	26.58
20	Confederation	15.23	10.44	25.68
21	Fleming	0.00	19.32	19.32
22	Northern	0	13.31	13.31
23	St. Lawrence	0	6.46	6.46
24	Boreal	0	3.41	3.41

Guided by a constructivist lens, this chapter scaffolded its analysis through successive stages—first isolating Governance (Will), then layering in Programs, Learners, Agreements, and Classification (Way). Each attribute was explored both as an independent signal and as part of a broader institutional learning ecosystem. In doing so, the TRI evolved not simply as a formulaic scorecard but as a constructivist discovery process: one that revealed patterns of strength, lag, and asymmetry across colleges as they prepare to transition into the AI era.

The chapter confirms that the TRI can serve not only as a benchmarking tool but also as a reflective instrument for institutional improvement. By breaking down complex readiness components into manageable, measurable elements, the framework aligns with the pedagogical spirit of Constructivism—allowing institutions to learn from comparative results, scaffold their own strategic improvements, and transition toward greater AI integration in an informed and equitable manner.

CHAPTER V
DISCUSSION

5.1 Discussion of Results

The weighted distribution of the Transition Readiness Index (TRI) revealed several key trends that reflect both the strengths and the disparities across Ontario's 24 publicly funded community colleges. Institutions can be broadly classified into four categories in AI Transitional Readiness.

Figure 5.1A
Distribution of Ontario Colleges by AI Transitional Readiness Quadrant

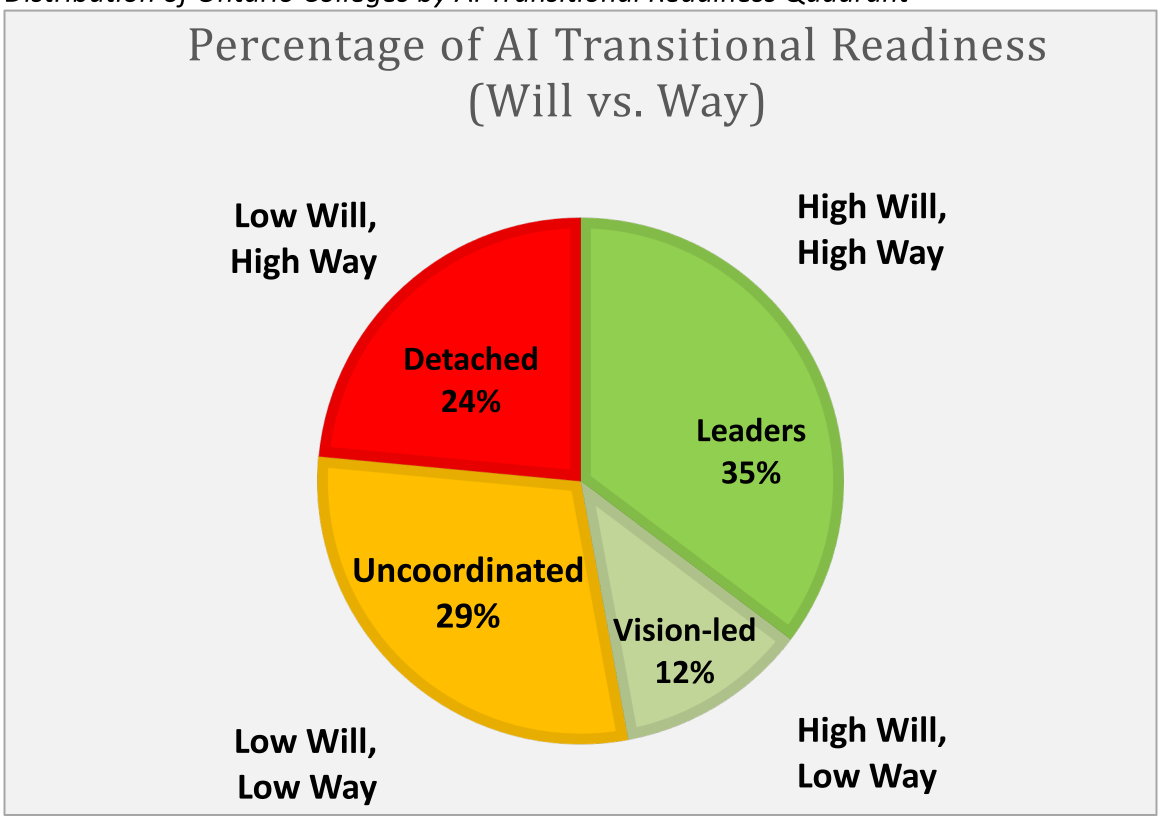


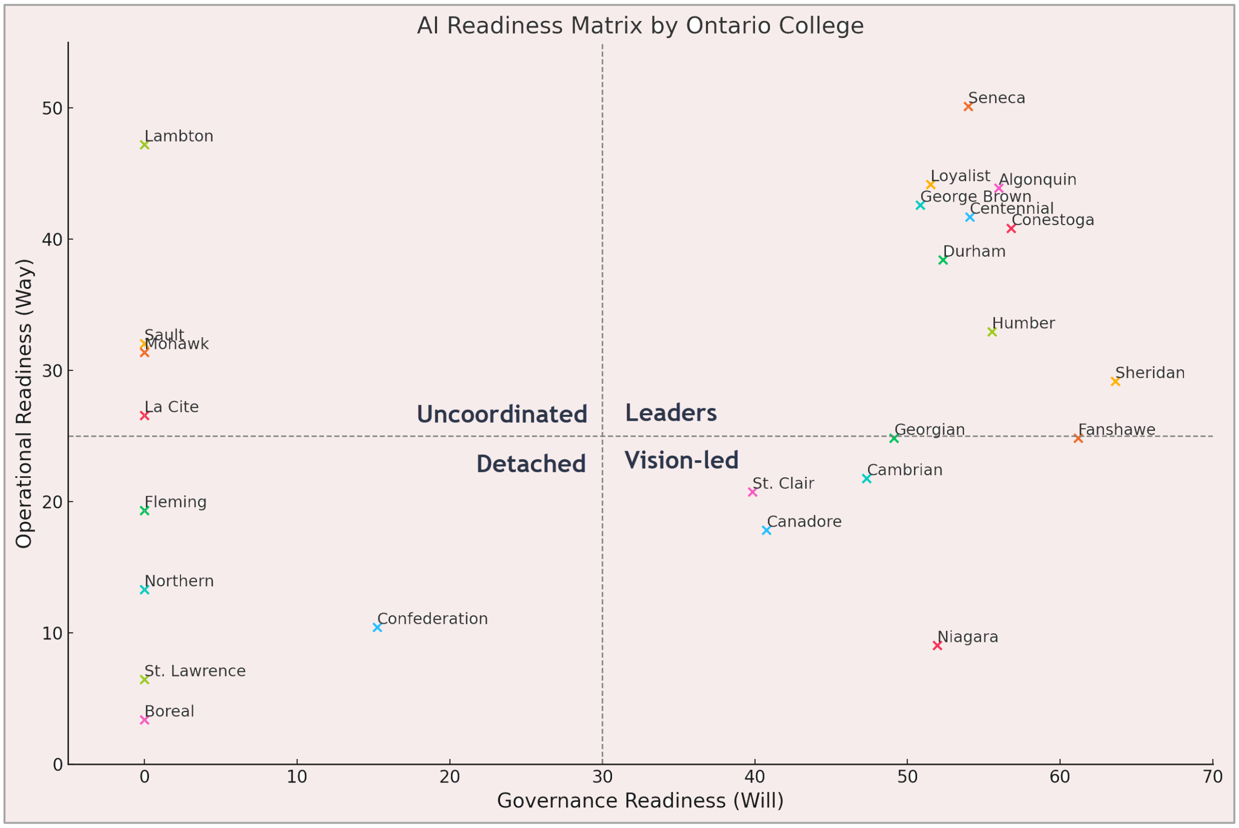
Figure 5.1A categorizes Ontario's 24 publicly funded community colleges into four readiness quadrants based on their TRI scores:

- High Will, High Way (Leaders)
- High Way, Low Will (Operational but Uncoordinated)
- Low Will, Low Way (Detached or Unprepared)
- High Will, Low Way (Strategically Oriented but Underdeveloped)

The distribution reflects the proportion of institutions demonstrating varying combinations of governance maturity ("Will") and operational capacity ("Way") in AI integration.

Figure 5.1B

Scattered Plot of College Position on the TRI Quadrant



As illustrated in Figure 5.1B, institutions such as Seneca, Algonquin, and Conestoga emerged as clear leaders in cumulative TRI performance. Their success is attributed to a balanced profile—combining robust AI governance frameworks with tangible programmatic and learner engagement, as well as documented strategic alignment through published mandate agreements and diverse CIP coverage. These institutions exemplify a holistic approach to AI readiness, wherein institutional "Will" (Governance) and "Way" (Operational Capacity) are strategically aligned.

Conversely, colleges such as Boreal, St. Lawrence, and Northern were found at the lower end of the readiness spectrum. However, their low TRI scores should not be hastily interpreted as a lack of institutional capacity. Rather, these results point to the absence of transparent AI governance policies, limited visibility of AI-related programming, or restricted articulation of strategic direction in the public domain. This distinction is essential. Within a Constructivist framework, institutional readiness is not a fixed attribute but an evolving construct—dependent not only on internal capacity, but also on the communicative scaffolding that signals preparedness to external audiences, including policymakers, employers, and learners.

The G-PLAC framework enabled this multi-layered assessment by assigning distributed weights to each domain of AI readiness: Governance (50%), Programs (12.5%), Learners (12.5%), Agreements (12.5%), and Classification (12.5%). Through this lens, the evolution of cumulative TRI scores across the study reflected an intentional scaffolding process, wherein each attribute contributed incrementally to the composite readiness index. As such, the results offer a constructivist snapshot of how colleges are positioning themselves along the AI readiness continuum—not solely through internal innovation, but also through the externalization and codification of their efforts.

This analysis reveals a secondary insight: that transparency, documentation, and alignment are as vital to readiness as the substantive resources and programming a college may possess. Colleges that underperform in the TRI may, in reality, be active in AI experimentation or faculty-led initiatives, yet suffer from a lack of centralized policy, clear governance structures, or cohesive public messaging. This reinforces the importance of institutional coherence and communicative clarity as readiness signals in the age of artificial intelligence.

5.2 Discussion of Research Question One

To what extent do Ontario's community colleges demonstrate strategic governance ("Will") in preparing for AI integration?

This dimension of readiness was operationalized through the Governance (G) component of the AI Transition Readiness Index (TRI), which accounted for 50% of each institution's final TRI score.

As illustrated in Figure 5.2, nearly one-third of colleges scored zero, indicating an absence of discoverable AI governance artifacts. This absence may not reflect internal inertia but instead highlights a lack of transparency or public communication—both essential signals of institutional commitment. The bimodal distribution of scores, validated through Gage R&R and Monte Carlo simulations, underscores a structural divide between colleges with clear governance strategies and those with minimal visible engagement.

Figure 5.2

Distribution of Governance Readiness Across Ontario Colleges

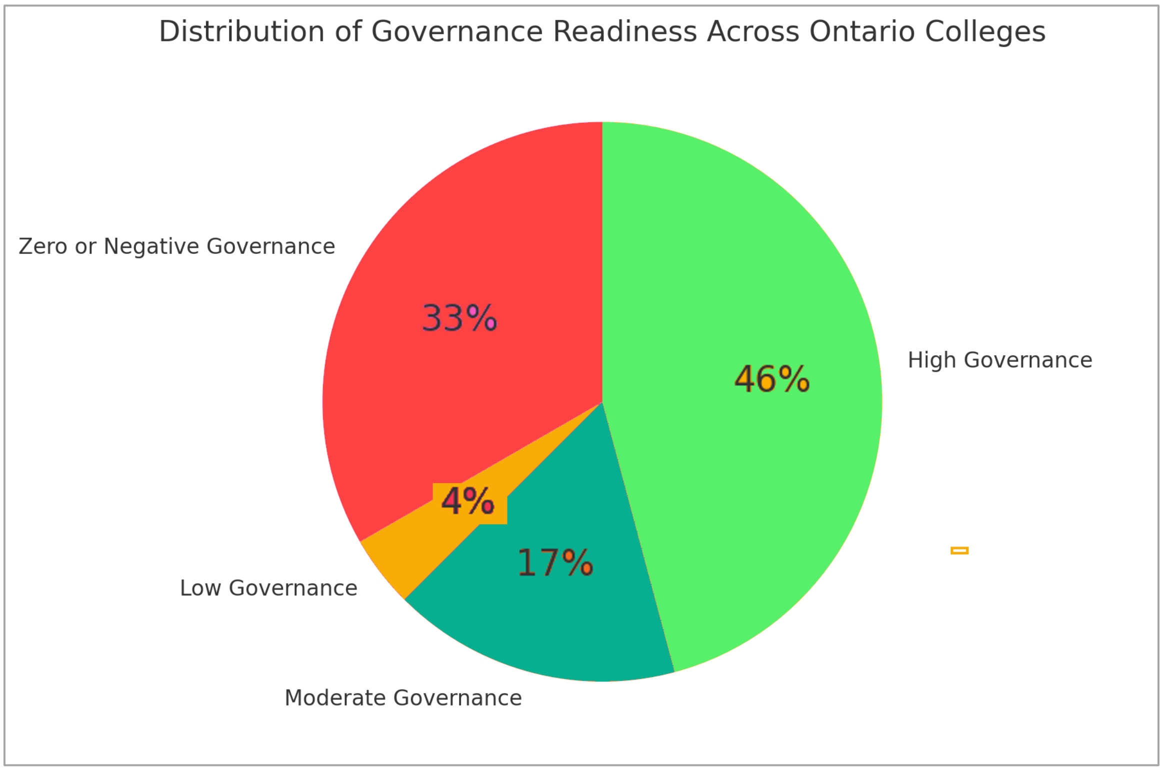


Figure 5.2 categorizes institutions into four tiers based on their normalized governance scores:

- **High Governance** (≥100)
- **Moderate Governance** (50–99)
- **Low Governance** (1–49)
- **Zero or Negative Governance** (0)

The findings from RQ1 suggest that while isolated exemplars of governance maturity exist within Ontario's college system, systemic gaps remain. These gaps appear less tied to capacity and more closely associated with issues of visibility, initiative, and public articulation. Given that the governance component alone contributes 50% of the TRI, institutions with strong policies but poor operational delivery (or vice versa) may still fall behind in overall AI readiness—highlighting the need for balanced development across both “Will” and “Way.”

This uneven distribution also raises broader questions about regulatory alignment, sector-wide expectations, and the role of leadership in navigating digital transformation. Without a provincial mandate or shared framework for AI governance, colleges risk advancing in silos, creating inconsistent experiences for learners and employers. RQ1 thus exposes both institutional differentiation and system-level fragmentation in Ontario’s approach to AI readiness.

5.3 Discussion of Research Question Two: Institutional Way – Operational Readiness via PLAC Attributes

To what extent do these colleges exhibit operational capacity (“Way”) to deliver AI-enabled educational outcomes?

Research Question Two examined the operational capacity—or "Way"—of Ontario’s 24 publicly funded community colleges in preparing for the AI transition. This capacity was measured through four distinct, quantifiable dimensions under the PLAC framework: Programs (P), Learners (L), Strategic Mandate Agreements (A), and Classification (C). Together, these attributes reflect each institution’s curricular offerings, learner engagement, policy alignment, and responsiveness to labour market signals—all critical to enacting an AI-enabled future.

Each PLAC attribute contributed equally (12.5%) to the AI Transition Readiness Index (TRI), complementing the 50% weight assigned to Governance (G). Unlike the Governance dimension, which reflects institutional intent and policy maturity, PLAC indicators focus on evidence of action—what colleges are tangibly doing in terms of programs offered, students enrolled, government commitments made, and disciplinary breadth aligned with AI workforce needs.

Programs (P) assessed the proportion of academic offerings that align with AI-related fields, using a curated CIP-39 taxonomy. Institutions such as Conestoga, Seneca, and Lambton emerged as leaders in program-level integration of AI themes. A high P score indicates a deep embedding of AI content across curricula, suggesting strategic program planning responsive to technological shifts.

Learners (L) evaluated the percentage and number of students enrolled in AI-aligned programs, reflecting demand-side engagement. Notably, colleges like George Brown and Loyalist recorded high L scores, indicating not only availability but also substantial uptake of AI-related learning opportunities. This learner demand signals early-stage normalization of AI education across institutional ecosystems.

Agreements (A) measured the degree to which Strategic Mandate Agreements (SMAs) referenced AI, machine learning, or related innovations. These government-submitted documents revealed wide variation in AI alignment, with only a handful of institutions—such as Seneca and George Brown—explicitly integrating AI into their SMA commitments. For most colleges, the A score remained modest, pointing to either a cautious strategic posture or the lag of policy commitments relative to curricular innovation.

Classification (C) quantified the diversity of AI-aligned CIP codes within each college's program inventory. High C scores—seen at institutions like Conestoga and Seneca—reflected curricular breadth, indicating a deliberate attempt to foster AI competencies across a wide array of disciplines. Conversely, low C scores suggest narrower specialization or early-stage exploration of AI relevance.

When considered collectively, the PLAC attributes reveal that strong operational capacity is not always matched by strong governance. For example, Lambton College, as illustrated in Figure 5.3, recorded one of the highest PLAC scores due to its rich program and learner engagement but scored zero on governance, highlighting a lack of visible policy scaffolding. This underscores a key insight from the PLAC analysis: capacity without coordination may signal risk, as strong delivery mechanisms need complementary governance for sustained impact.

Figure 5.3

Stacked TRI Contributions by G-PLAC Attribute, Ontario Colleges

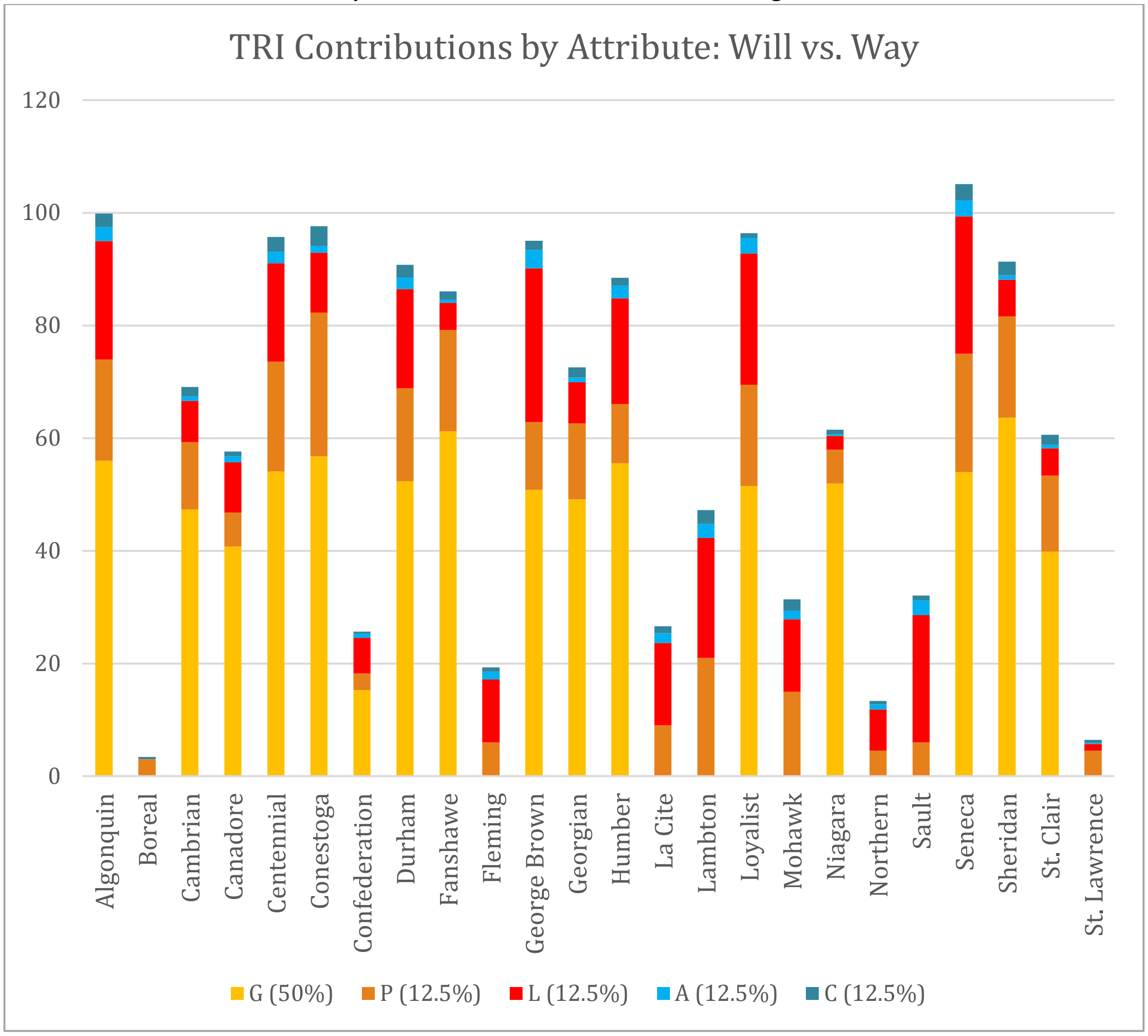


Figure 5.3 shows the proportional contribution of each G-PLAC attribute (Governance, Programs, Learners, Agreements, Classification) to the overall Transition Readiness Index (TRI) for each of Ontario's 24 community colleges. Lambton's profile illustrates a significant operational commitment (high PLAC) without a corresponding governance structure (G = 0), highlighting a Way–Will imbalance.

Conversely, a few institutions showed balanced performance across both G and PLAC dimensions. Seneca College, for instance, ranked near the top in all five TRI components, signaling a comprehensive readiness model that combines intent with execution.

Ultimately, the PLAC discussion supports a more nuanced understanding of institutional AI readiness. It shows that while some colleges may lack formal governance documentation, their operational structures are already moving toward AI integration. Others may have policy blueprints but face challenges in executing them through programs and learner engagement. This distinction between "Will" and "Way" is foundational to the G-PLAC framework and is essential for informing strategic interventions, funding prioritization, and institutional benchmarking.

5.4 Discussion of Research Question Three

RQ3: How does AI readiness in Ontario colleges compare to global best practices as observed in the QS World Top 10 AI universities?

In parallel to the provincial analysis, the QS World Top 10 AI Universities provided a stable, high-performing reference group. For the Governance dimension, a direct Top 10 achieved an average Governance score of 37.08, with most institutions demonstrating high-scoring reproducibility, low defect rates, and Sigma Tiers of 5σ to 6σ. Institutions such as Harvard, MIT, ETH Zurich, and NUS scored consistently above 35/50 with minimal variation, reflecting deep institutional investment in AI governance infrastructure.

By contrast, the Ontario college average was 21.66, with only two colleges surpassing the global mean. Many Ontario institutions lacked publicly available policies, producing Final Governance scores of zero and low Sigma classifications (≤3σ). This discrepancy highlights a significant gap in policy maturity, not necessarily in innovation or experimentation, but in formal governance intent. This finding, underscores the relevance of the Will–Way bifurcation in the TRI framework.

While several Ontario colleges exhibit operational readiness through active programming and learner engagement, their strategic governance commitment lags behind global best practices. The Governance dimension thus provides a reliable diagnostic baseline for identifying readiness gaps and guiding institutional development in a rapidly evolving AI landscape.

Table 5.4
Comparative Governance Scores, DPMO, and Sigma Tiers for QS World Top 10 and Ontario 24

Rank	Institution	Average Governance Score	Defects per Million Opportunities	Sigma Tier	
1	Harvard University	44.96	0	6σ	
2	University of Toronto	43.52	12	5σ	
3	Sheridan	41.1	110	5σ	
4	Fanshawe	39.52	240	4σ	
5	Carnegie Mellon University	39.5	476	4σ	World
6	University of California, Berkeley	37.26	14	5σ	Top 10
7	Conestoga	36.72	199	5σ	Average
8	University of Oxford	36.38	5,583	4σ	(37.08)
9	Algonquin	36.28	1,561	4σ	
10	ETH Zurich	36.04	0	6σ	
11	Humber	35.86	23,441	3σ	
12	Centennial	34.94	9,869	3σ	
13	Seneca	34.86	0	6σ	
14	Massachusetts Institute of Technology (MIT)	34.86	0	6σ	
15	National University of Singapore (NUS)	33.96	0	6σ	
16	Durham	33.84	368	4σ	
17	Niagara	33.58	20,439	3σ	
18	Loyalist	33.26	0	6σ	
19	George Brown	32.86	0	6σ	Adjusted
20	Nanyang Technological University (NTU)	32.8	50,031	3σ	Ontario
21	Georgian	31.72	191	5σ	Average
22	Hong Kong University of Science and Technology	31.5	17,223	3σ	(32.30)
23	Cambrian	30.68	3	6σ	
24	Canadore	26.32	42,811	3σ	Actual
25	St. Clair	25.74	22,178	3σ	Ontario
26	Confederation	9.84	88,454	2σ	Average
27	Lambton	3	0	0	(21.66)
28	Fleming	0	0	0	
29	Boreal	-0.72	0	0	
30	La Cite	-1.32	6	0	
31	Mohawk	-1.32	8	0	
32	Sault	-2.52	394	0	
33	St. Lawrence	-3.68	1398	0	
34	Northern	-3.76	23182	0	

	World Top 10 Average	**37.08**		
	Actual Ontario Average	21.66		
	Adjusted Ontario Average	**32.30**		

To ensure methodological fairness, institutions with raw governance scores of near zero or less were excluded from the normalization mean. These lows signify either complete policy absence or non-discoverability and thus do not reflect measurable intent or effort. This exclusion ensures that normalized scores reflect meaningful governance engagement rather than artifacts of omission.

In summary, the findings confirm that although AI governance is gaining momentum in a small number of Ontario colleges, the sector as a whole remains in an early stage of policy formalization. This underscores the importance of treating governance as a distinct construct in readiness assessment and affirms the need for reproducible, rubric-based diagnostics in tracking institutional "Will."

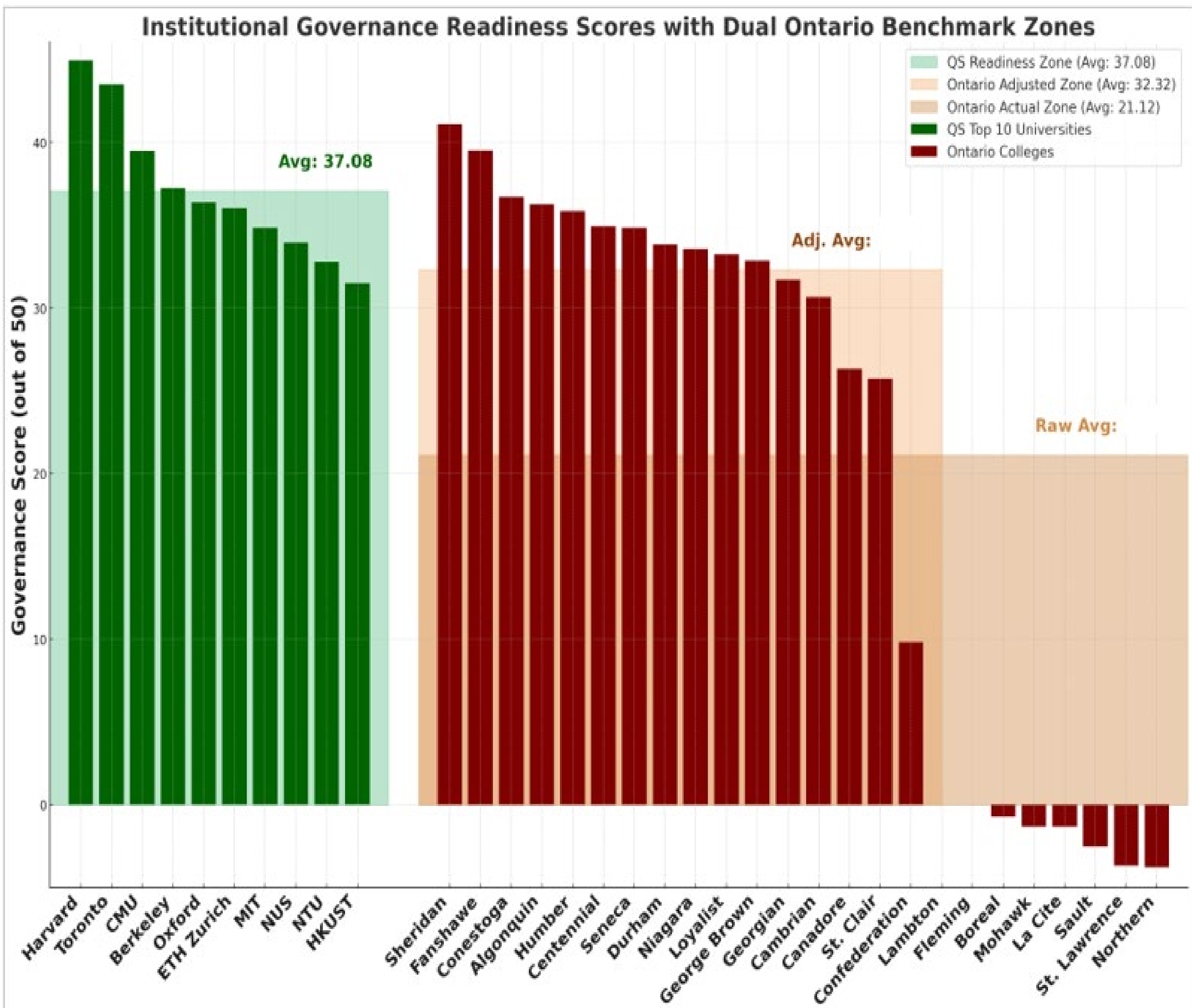
Comparing the average Governance readiness scores—37.08 for the QS Top 10 AI universities versus 21.66 for Ontario's 24 colleges, on a standardized 50-point rubric—yields a quantifiable measure of the maturity gap between the two sectors. This 43% differential relative to the maximum benchmark highlights a substantial divide not only in policy documentation but in strategic intentionality, governance infrastructure, and institutional transparency.

To account for outliers and zero-scoring institutions, a normalized average was also computed using only non-zero Ontario colleges. This adjusted cohort benchmark yields a higher Governance score of 32.30, narrowing the apparent gap to approximately five points. However, this adjusted value should not obscure the systemic absence of formal governance mechanisms in nearly one-third of Ontario's colleges. The coexistence of a raw average (21.66) and an adjusted average (32.30) thus reflects both the sector's emerging strengths and its persistent foundational gaps.

Elite global institutions, such as Harvard, ETH Zurich, and MIT, routinely scored above 35 and achieved Sigma Tiers of 5σ or 6σ, reflecting highly stable, well-articulated AI policies. In contrast, many Ontario colleges remain in a pre-formalization phase, lacking institution-wide declarations or reproducible governance artifacts. While some institutions show promise through isolated AI programs or experimental practices, the governance disparity confirms that operational experimentation (“Way”) is not a substitute for formalized institutional intent (“Will”).

In sum, the 15.42-point gap between global and provincial raw averages—and the narrower 4.78-point gap using adjusted values—underscore the need for dual benchmarking logic within the AI Transition Readiness Index (TRI). By separately tracking raw and adjusted governance benchmarks, the TRI can reveal both the sector-wide urgency for 0 improvement and the pathways already emerging among early adopters. These insights strengthen the case for accelerating policy codification across Ontario’s college sector to ensure readiness is both operational and intentional.

Figure 5.4.1
Comparative Governance Readiness Scores and Benchmark Zones—QS Top 10 AI Universities vs Ontario Colleges



5.5 Discussion on Research Question Four

RQ4: Can a reproducible AI readiness index, grounded in rubric-constrained and data-validated methods, serve as a diagnostic benchmarking tool for policymakers and academic leaders?

This study provides compelling evidence that the AI Transition Readiness Index (TRI)—underpinned by the G-PLAC framework and rigorously implemented through deterministic scoring and data-mined metrics—functions not only as a summative measure but as a diagnostic tool. It offers three distinct advantages in this role: baseline benchmarking, internal balance assessment, and alignment with labour market demands.

5.5.1 2025 as a Baseline Year – Establishing a Reference Point. The AI Transition Readiness Index (TRI) adopts 2025 as its inaugural baseline year, assigning Ontario's normalized institutional average a value of 100. This calibration establishes a reference point from which institutional trajectories can be monitored over time and compared across jurisdictions. By setting a fixed baseline, the TRI creates the conditions for longitudinal tracking, revealing whether individual institutions—and the system as a whole—are progressing, regressing, or plateauing in their readiness to support AI-enabled teaching and learning.

Colleges that score well above the 100 mark may be seen as potential leaders in AI transition planning, while those scoring below the provincial average may warrant targeted policy support, governance strengthening, or capacity-building interventions. Importantly, the TRI is not a pass/fail mechanism, but a comparative yardstick that promotes reflection, planning, and continuous improvement.

The 2025 baseline also enables cross-sectoral and geographic comparisons, allowing Ontario's community colleges to be benchmarked against universities, polytechnics, or peer institutions in other provinces and countries. Because the TRI assigns equal weighting to Governance (G) and Operational Readiness (PLAC), it ensures a balanced emphasis on both strategic policy intent and practical implementation—capturing not just what institutions say, but what they do.

As the model evolves in future years, it may incorporate additional diagnostic thresholds to sort institutions into performance tiers such as World-Class, Emerging, At-Risk, or Unready, thereby aiding both institutional leaders and policymakers in prioritizing resource allocation and reform efforts.

Table 5.5.1
Midpoint Normalized TRI Scores for Ontario Colleges (2025 Baseline Year = 100)

Ranking	Institution	TRI (G) 50%	TRI (PLAC) 50%	Sub-total	Midpoint Normalized	TRI Score (Baseline =100)
1	Seneca	53.97	51.11	105.08	193.71	171.22
2	Algonquin	55.98	43.88	99.86	184.09	162.71
3	Conestoga	56.79	40.81	97.60	179.92	159.03
4	Loyalist	51.49	44.87	96.36	177.64	157.01
5	Centennial	54.06	41.66	95.72	176.46	155.97
6	George Brown	50.84	44.18	95.02	175.17	154.83
7	Sheridan	63.63	27.70	91.33	168.37	148.81
8	Durham	52.33	38.43	90.76	167.31	147.88
9	Humber	55.52	32.93	88.45	163.06	144.12
10	Fanshawe	61.19	24.84	86.03	158.60	140.18
11	Georgian	49.11	23.47	72.58	133.80	118.26
12	Cambrian	47.31	21.78	69.09	127.37	112.58
–	**Ontario Average**		**–**	**61.48**	**113.14**	**100.00**
13	Niagara	51.93	9.55	61.48	113.34	100.18
14	St. Clair	39.85	20.75	60.60	111.72	98.74
15	Canadore	40.75	16.85	57.60	106.18	93.85
16	Lambton	0.00	47.20	47.20	87.01	76.91
17	Sault	0.00	32.05	32.05	59.08	52.22
18	Mohawk	0.00	31.37	31.37	57.83	51.11
19	La Cité	0.00	26.58	26.58	49.00	43.31
20	Confederation	15.23	10.44	25.67	47.32	41.83
21	Fleming	0.00	19.32	19.32	35.62	31.48
22	Northern	0.00	13.31	13.31	24.54	21.69
23	St. Lawrence	0.00	6.46	6.46	11.91	10.53
24	Boreal	0.00	3.41	3.41	6.29	5.56

Table 5.5.1 presents TRI results for Ontario's 24 publicly funded community colleges. The TRI is composed of two equally weighted components: Governance (G) and Operational Capacity (PLAC), with each accounting for 50% of the composite score. The subtotal is midpoint-normalized and scaled to an average score of 100 to allow fair cross-institutional comparisons. Institutions scoring above 100 are performing above the 2025 provincial baseline, while those below 100 may face barriers in strategic readiness, operational delivery, or both.

While the TRI offers a cumulative measure of institutional readiness, its real diagnostic power lies in the internal disaggregation of Governance and Operational components. By examining the relationship between strategic will (G) and executional capacity (PLAC), institutions can identify structural imbalances that might otherwise remain obscured in aggregate scores. The following section explores this dynamic through a Governance-to-PLAC ratio, offering a lens into how well-aligned each institution is in translating AI strategy into action.

5.5.2 G:PLAC Ratio – Assessing Internal Balance Between Will and Way. Beyond aggregate TRI rankings, the G-PLAC framework supports institution-level diagnostics by evaluating the ratio of Governance ("Will") to PLAC ("Way"). This G:PLAC ratio reveals internal alignment—or misalignment—between policy intent and execution capacity in advancing AI readiness.

A G:PLAC ratio greater than 1.0 indicates that the institution's strategic governance outpaces its operational implementation. In such cases, the gap may reflect aspirational planning without sufficient follow-through, requiring investment in programs, learner outreach, or systems integration. Conversely, a ratio near zero signals that AI-related activity is occurring without a public governance framework—a potential red flag for inconsistency, ethical oversight gaps, or lack of institutional accountability.

Table 5.5.2
Governance-to-Implementation (G:PLAC) Ratios by Institution

Institution	TRI (G) 50%	TRI (PLAC) 50%	G:PLAC Ratio
Niagara	51.93	9.55	5.44
Fanshawe	61.19	24.84	2.46
Canadore	40.75	16.85	2.42
Sheridan	63.63	27.7	2.30
Cambrian	47.31	21.78	2.17
Georgian	49.11	23.47	2.09
St. Clair	39.85	20.75	1.92
Humber	55.52	32.93	1.69
Confederation	15.23	10.44	1.46
Conestoga	56.79	40.81	1.39
Durham	52.33	38.43	1.36
Centennial	54.06	41.66	1.30
Algonquin	55.98	43.88	1.28
George Brown	50.84	44.18	1.15
Loyalist	51.49	44.87	1.15
Seneca	53.97	51.11	1.06
Lambton	0	47.2	0.00
Sault	0	32.05	0.00
Mohawk	0	31.37	0.00
La Cité	0	26.58	0.00
Fleming	0	19.32	0.00
Northern	0	13.31	0.00
St. Lawrence	0	6.46	0.00
Boreal	0	3.41	0.00

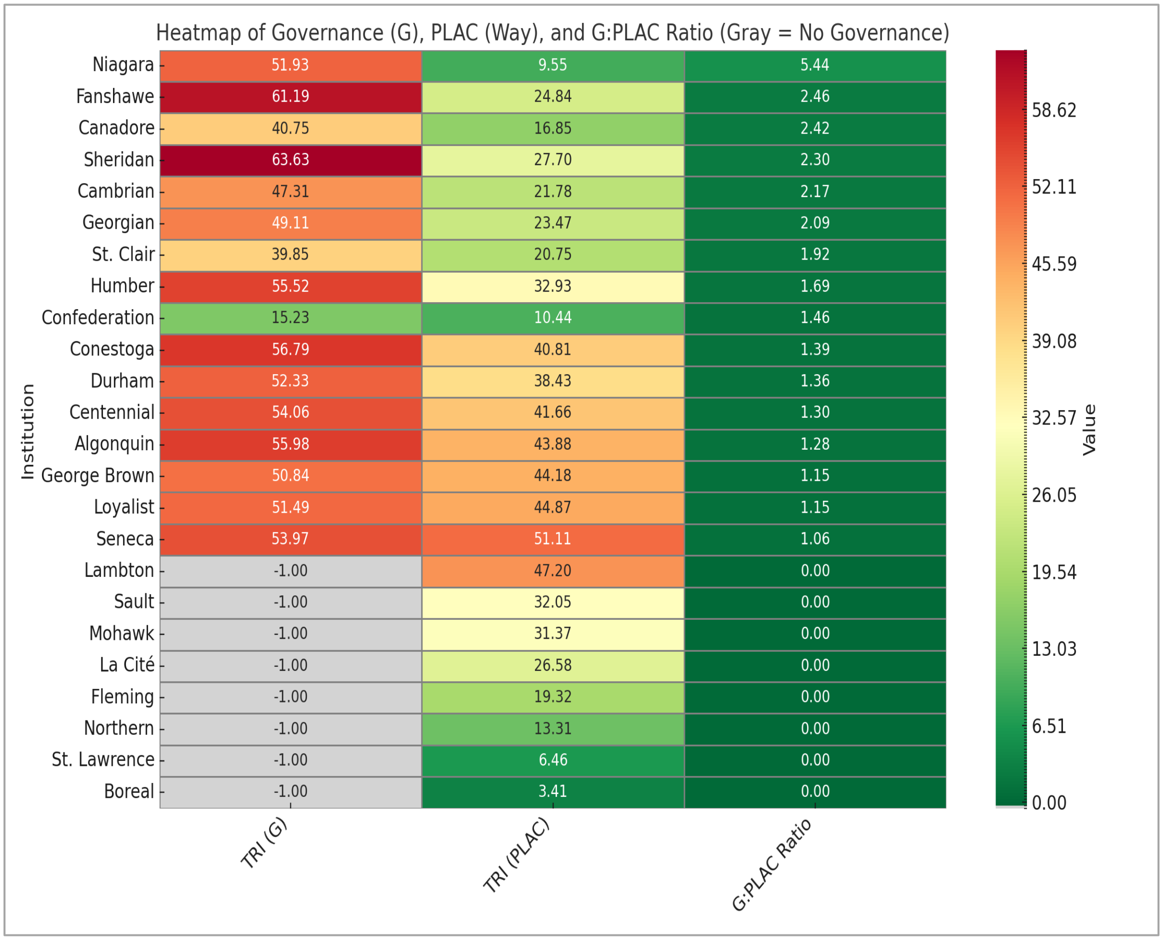
While not a definitive measure of readiness, the ratio acts as a strategic early warning signal, prompting administrators to review how well their vision is being translated into action. Ideally, institutions should approach a G:PLAC ratio of 1.0, signifying a balanced trajectory between Will and Way.

A visual heatmap, showing Governance (G), Operational Capacity (PLAC), and the G:PLAC Ratio, offers more insights. Deep red indicates significant over-governance;

green denotes balanced alignment; gray reflects implementation without public-facing governance structures.

Figure 5.5.2

Heatmap of G:PLAC Ratios Across Ontario Colleges



Interpretation for Figure 5.5.2 (Heatmap)

- **Deep red (left column):** High governance intent (G) — e.g., Sheridan, Fanshawe, Conestoga.
- **Lighter greens in PLAC:** Moderate or low implementation readiness.
- **Dark green in Ratio column:** High imbalance between Will and Way — especially Niagara (5.44) and Fanshawe (2.46).
- **Gray zone (0 G:PLAC): I**nstitutions implementing AI without public-facing governance — Lambton, Mohawk, La Cité, etc.

5.5.3. Market Alignment – Comparing Learner Engagement with National AI Labour Demand. The "L" attribute of the PLAC framework captures the percentage of learners enrolled in AI-aligned programs within Ontario's public community colleges. For the 2023–2024 academic year, this share averaged 11.4%, based on enrollment data filtered using a curated AI-relevant CIP code taxonomy. While this statistic signals meaningful institutional engagement with AI curricula, it should not be interpreted as a comprehensive measure of societal readiness for AI.

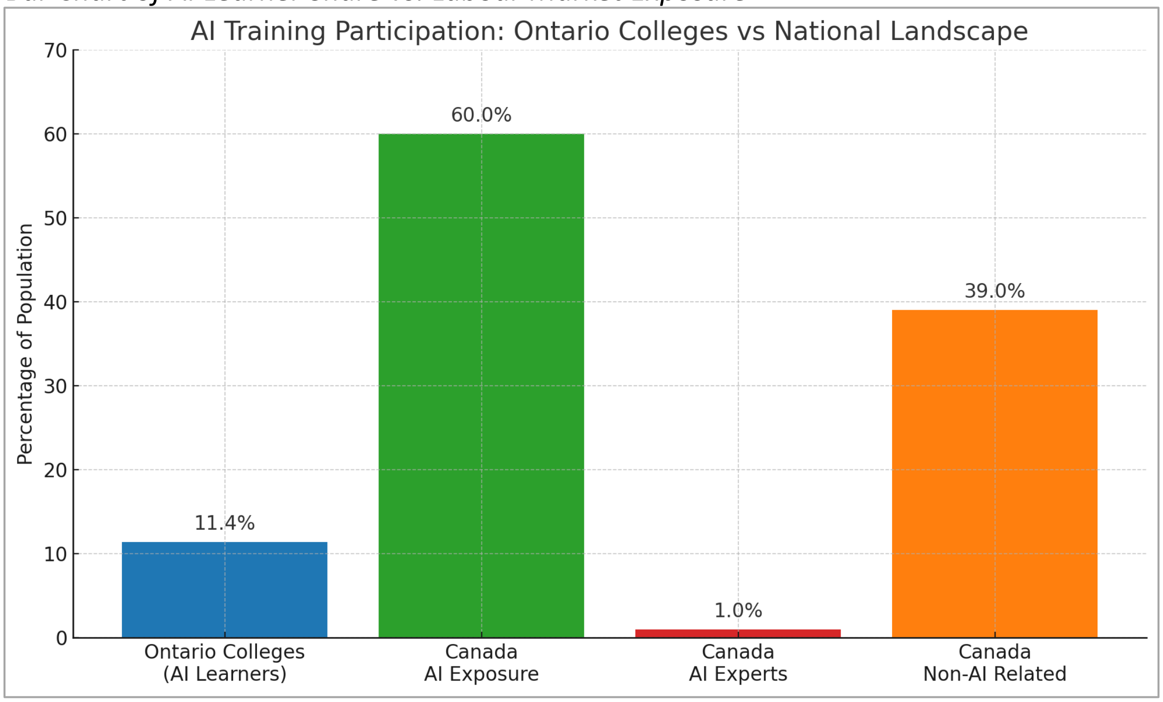
To contextualize the relevance of this learner share, it must be viewed in relation to broader national labour market trends. A 2024 Statistics Canada study found that 60% of Canadian occupations are exposed to AI-driven transformation, although the majority are expected to be complemented by, rather than replaced by, AI technologies (Statistics Canada, 2024b). These AI-exposed occupations span all sectors—from healthcare and finance to skilled trades and education—indicating the systemic nature of the transition.

However, only a small fraction of jobs requires deep AI-specific expertise. According to another Statistics Canada report, just 1% of job postings between 2018 and 2023 explicitly demanded advanced AI skills such as machine learning, neural networks, or computer vision (Statistics Canada, 2024c). This highlights a key distinction between AI awareness and AI specialization, both of which require different institutional responses.

Interpreting the 11.4% AI Learner Share. Against this backdrop, Ontario's 11.4% AI learner average should be interpreted as directionally significant, but not definitive. While it exceeds the 1% of roles requiring specialist AI skills, it falls far short of the 60% of roles broadly exposed to AI. This suggests that community colleges are actively investing in AI curriculum development, but more work is needed to reach the full breadth of the labour market's evolving needs.

Moreover, community colleges are not the only institutions contributing to AI skill formation. Universities, MOOCs, private bootcamps, and foreign credential providers all play a role in preparing workers for AI-integrated environments. Therefore, a single-year enrollment figure offers limited predictive power. Instead, it serves as a proxy for institutional capacity and direction, rather than a summative measure of learner preparedness or labour market alignment.

Figure 5.5.3
Bar Chart of AI Learner Share vs. Labour Market Exposure



The visualization highlights a potential gap between institutional training capacity and the scale of AI transformation within the labour market.

Caution on Over-Attribution. This study refrains from treating AI learner share as a readiness score. Many workers acquire AI literacy through prior years, non-formal learning, or in-service training. Thus, institutional AI enrollment is best used as an annual indicator of curricular orientation, not a proxy for total system sufficiency.

5.6 Conclusion to Discussion Chapter

This discussion has demonstrated that a reproducible AI Transition Readiness Index (TRI), grounded in rubric-constrained scoring and data-validated benchmarks, offers a credible and diagnostic framework for assessing institutional preparedness. The TRI captures both the "Will"—through AI governance maturity—and the "Way"—via operational indicators under the PLAC framework.

Ontario's average TRI score, anchored at 100, establishes a provincial baseline against which future institutional progress can be measured longitudinally or compared across jurisdictions. Institutions with a high Governance-to-PLAC ratio exhibit strong policy ambition but may lack sufficient infrastructure or programs to translate vision into practice. Conversely, those with robust PLAC scores but underdeveloped governance risk operational drift and regulatory misalignment.

Also, by integrating national labour market indicators—such as AI job exposure and expertise requirements—the TRI model contextualizes institutional readiness within broader workforce dynamics. This dual perspective reinforces the utility of the TRI not only as an internal planning tool for colleges, but also as an evidence-based benchmark for policymakers, funders, and academic leaders.

In summary, the TRI advances the field of educational AI benchmarking by offering a transparent, replicable, and diagnostically meaningful measure of readiness. Its application across Ontario's 24 community colleges establishes a foundation for future research, iterative policy refinement, and continuous institutional improvement in the age of artificial intelligence.

CHAPTER VI:
SUMMARY, IMPLICATIONS AND RECOMMENDATIONS

6.1 Summary of Key Findings

This study set out to evaluate how Ontario's 24 publicly funded community colleges are preparing for the transition to an AI-integrated educational landscape. Through the construction and application of the AI Transition Readiness Index (TRI), which combines rubric-constrained scoring with data-validated attributes across governance and operational dimensions, the following findings emerged:

RQ1: To what extent do Ontario's community colleges demonstrate strategic governance ("Will") in preparing for AI integration?

The Governance (G) dimension revealed substantial variation across institutions. While a few colleges—such as Seneca and Conestoga—exhibited proactive governance models, including public AI policies and dedicated leadership structures, many lacked formalized strategies or transparent implementation plans. The rubric-driven evaluation highlighted gaps in accountability, public accessibility, and staff inclusion, suggesting that institutional "Will" remains underdeveloped relative to the pace of AI's societal impact.

RQ2: To what extent do these colleges exhibit operational capacity ("Way") to deliver AI-enabled educational outcomes?

Operational readiness, measured through the PLAC framework (Programs, Learners, Agreements, Classification), presented a more encouraging picture. Colleges such as Lambton and Centennial demonstrated strong curricular integration of AI-relevant programs. Learner engagement with AI-focused offerings was non-trivial, with Ontario colleges accounting for 11.4% of AI learners nationally. However, alignment with government strategic mandates (Agreements) and disciplinary breadth (Classification) was uneven. Institutions with high PLAC scores often lacked matching governance maturity, indicating operational activity without clear policy scaffolding.

RQ3: How does AI readiness in Ontario colleges compare to global best practices as observed in the QS World Top 10 AI universities?

The benchmarking exercise revealed a readiness gap between Ontario colleges and the world's leading AI universities. While elite institutions such as Stanford, MIT, and NUS demonstrated fully integrated AI ecosystems—complete with policies, faculty expertise, interdisciplinary programs, and experiential learning pathways—Ontario colleges exhibited fragmented efforts. This finding underscores the need for coordinated strategic planning and investment if Ontario is to remain competitive in the AI-driven global education landscape.

RQ4: Can a reproducible AI readiness index, grounded in rubric-constrained and data-validated methods, serve as a diagnostic benchmarking tool for policymakers and academic leaders?

The development and application of the TRI model proved effective in providing a transparent, reproducible, and scalable diagnostic tool. By anchoring the Ontario average at 100, the model enables both intra-provincial comparison and international benchmarking. The deterministic scoring method—validated through Gage R&R and Monte Carlo simulation—adds statistical robustness. As such, the TRI model holds promise for institutional planning, public accountability, and longitudinal monitoring of AI readiness in postsecondary education.

6.2 Implications for Policy and Practice

The findings of this study carry significant implications for multiple stakeholders within Ontario's postsecondary education ecosystem, particularly as artificial intelligence continues to reshape pedagogical practices, curriculum design, institutional accountability, and workforce development.

6.2.1 Implications for Senior Academic Leaders. College presidents, vice-presidents academic, deans, and departmental chairs are urged to treat AI readiness as both a strategic imperative and an operational priority. Institutions demonstrating high operational activity (PLAC) but weak governance (G) risk inconsistency, reputational vulnerability, and ethical blind spots. Strengthening AI governance structures—such as formal task forces, public policies, or staff inclusion mechanisms—can reinforce institutional credibility and ensure alignment between intent and execution. Leaders should also embed AI readiness within broader strategic planning and quality assurance processes.

6.2.2 Implications for Faculty and Curriculum Designers. Instructors and curriculum developers play a central role in actualizing institutional AI readiness. The observed misalignment between AI program offerings and governance maturity suggests that much of the innovation is occurring at the instructional level without formal institutional endorsement. Faculty should be supported through professional development in AI literacy, ethical frameworks, and generative tools. Moreover, curriculum renewal should move beyond technical programs to embed AI ethics, digital fluency, and algorithmic thinking across all disciplines, fostering inclusive AI preparedness.

6.2.3 Implications for Policymakers and System Planners. At the provincial level, the Ministry of Colleges and Universities (MCU) and its affiliated agencies should consider integrating AI readiness metrics into funding envelopes, quality assurance audits, and mandate agreement renewals. The AI Transition Readiness Index (TRI) provides a scalable model for such benchmarking. Policymakers may also consider developing a provincial AI governance standard or charter for the college sector, modeled after similar efforts in data governance or equity, diversity, and inclusion. This would reduce fragmentation and incentivize coordinated progress across the system.

6.2.4 Implications for Employers and Workforce Developers. Employers increasingly expect graduates to possess AI fluency, even in non-technical roles. As such, workforce development agencies and industry partners should deepen collaboration with colleges to co-design micro-credentials, experiential learning opportunities, and responsive curricula. The study’s finding that only 1% of Canadian jobs currently require advanced AI expertise, while 60% are AI-exposed, supports the case for broad-based digital upskilling rather than narrow specialization. Colleges are uniquely positioned to fulfill this societal need if properly resourced and strategically guided.

6.3 Limitations of the Study

While the development and application of the AI Transition Readiness Index (TRI) have provided valuable insights into the AI preparedness of Ontario's community colleges, several limitations should be acknowledged to contextualize the scope and interpretation of the findings.

6.3.1 Reliance on Publicly Available Data by Design. The TRI model was intentionally constructed using only publicly accessible documents—such as institutional websites, AI policy pages, program inventories, and government datasets—to ensure transparency, replicability, and alignment with the principle of open benchmarking. However, this design choice also introduces limitations. Institutions with substantive but unpublished or internally archived initiatives may appear less prepared than they are in practice. As such, the TRI reflects a college's outward-facing readiness and policy visibility rather than the totality of internal actions or intent.

6.3.2 Incomplete or Inaccessible Governance Content. Several colleges published their AI guidelines only in non-machine-readable formats (e.g., scanned PDFs) or hosted them on restricted-access intranet sites. Although steps were taken to parse these documents using both HTML and PDF scraping methods, technical constraints may have excluded relevant governance indicators from scoring. This introduces a potential bias in the Governance (G) dimension, despite deterministic evaluation criteria.

6.3.3 Static Evaluation of a Rapidly Evolving Domain. The TRI provides a snapshot in time—anchored to the 2024–2025 academic year—of a dynamic and fast-evolving field. Given the accelerating pace of AI adoption and regulatory development, some institutions may have implemented substantive changes after the cutoff date of data collection. This temporal limitation is inherent to benchmarking studies and highlights the importance of longitudinal follow-up.

6.3.4. Omission of Experiential Learning (X) in Final Index Construction. Although the original G-PLANET-X framework explicitly included Experiential Learning (X) as a critical dimension of AI readiness, it was excluded during the realignment to the final G-PLAC model due to the absence of standardized, system-wide metrics. Unlike other attributes, experiential learning lacks a uniform provincial benchmark across Ontario's community colleges. As a result, the TRI does not currently evaluate the quality, frequency, or integration of work-integrated learning, co-ops, or AI-focused capstone projects. This omission reflects a practical constraint rather than a conceptual oversight. Notably, experiential learning remains a priority for future measurement and could be formally incorporated with the next round of Strategic Mandate Agreements (SMAs), slated to begin in 2026.

6.3.5 Generalizability Beyond Ontario. The model was calibrated for Ontario's publicly funded colleges and aligned to provincial policy structures. While the TRI has potential for adaptation beyond this context, its current formulation may not fully account for jurisdictional differences in governance, curriculum autonomy, or accountability frameworks present in other provinces or countries.

6.4 Recommendations for Future Research

The findings of this study open several promising avenues for future research, particularly as institutions, governments, and scholars continue to grapple with the complex implications of artificial intelligence for postsecondary education. The following recommendations are offered to extend, deepen, and institutionalize the work initiated through the development of the AI Transition Readiness Index (TRI).

6.4.1 Repatriation of the Study to Ontario. While this doctoral research was successfully incubated within a global context through the Swiss School of Business and Management (SSBM), long-term sustainability and relevance would be enhanced by repatriating the TRI model to an Ontario-based academic or policy institution. The 2025 edition of this study serves as the benchmark year, with the TRI index scaled to a provincial average of 100. Repatriation would enable the institutionalization of the TRI as an annualized diagnostic initiative, allowing for the accumulation of comparative historical data over time. This would support evidence-based policymaking, enable the monitoring of longitudinal trends in AI readiness, and ensure timely responsiveness to evolving pedagogical and technological developments. Hosting the TRI within Ontario would also increase legitimacy, encourage collaboration across colleges and government bodies, and provide a durable mechanism for continuous improvement.

6.4.2 Expansion of the TRI Framework to Ontario's Public Universities. This study focused exclusively on Ontario's 24 publicly funded community colleges. A sibling study that applies a modified TRI framework to Ontario's 22 publicly funded universities could yield valuable comparative insights. Such a study may require recalibration of the rubric and attribute weights to account for the research-intensive missions of universities. New indicators might include measurements of AI research output, faculty citation indices in AI-relevant fields, and the presence of interdisciplinary AI research centres. This comparative dimension would enable a holistic provincial picture of AI readiness across the postsecondary sector.

6.4.3 Development of the AI-EdBOK: A Body of Knowledge for AI in Education. A significant byproduct of this study is the conceptual groundwork for a Body of Knowledge for Artificial Intelligence in Education (AI-EdBOK). Inspired by the Project Management Institute's PMBOK, the AI-EdBOK would formalize the theoretical foundations, framework logic, and methodological tools required to assess AI readiness in educational contexts. Its proposed structure includes pedagogical foundations (e.g., Connectivism and ConnectivAI), diagnostic frameworks (e.g., G-PLAC, TRI), and applied tools (e.g., rubrics, statistical validation methods, and AI governance rubrics). Formalizing the AI-EdBOK through collaborative academic efforts could create a shared reference architecture for AI transformation in postsecondary education worldwide.

6.5 Final Remarks

This dissertation set out to explore how Ontario's community colleges are preparing for the profound transition brought about by artificial intelligence in teaching, learning, and workforce development. In response to this challenge, the AI Transition Readiness Index (TRI) was developed as a rubric-constrained, data-validated diagnostic tool, capable of capturing both the Will (governance) and Way (operational readiness) of institutions across multiple dimensions.

The study revealed uneven levels of preparedness across the sector, with a small subset of colleges emerging as early leaders and others showing limited strategic coordination or transparency. Yet it also surfaced encouraging signs—innovative programs, engaged learners, and alignment with broader labour market signals—suggesting that the foundation for a province-wide AI transformation is already forming.

Perhaps most importantly, the research demonstrates that it is possible to measure AI readiness in a reproducible and rigorous manner, using publicly available data, deterministic methods, and transparent evaluation logic. The TRI model offers not only a snapshot of current institutional capacity but also a roadmap for continuous improvement. As Ontario's postsecondary system navigates the unfolding AI era, such tools will be critical to ensuring that policy, pedagogy, and institutional design evolve in tandem with technological change.

Going forward, the TRI model can serve as a living diagnostic framework—one that evolves with the field, deepens with historical data, and expands to other educational contexts, including universities and international comparators. The future of AI in education should not be left to speculation or siloed innovation. It demands structured inquiry, sustained benchmarking, and an ethical commitment to inclusive and forward-looking governance.

In that spirit, this dissertation offers not just a set of findings, but a replicable methodology, a conceptual framework, and a scholarly foundation for a broader AI-EdBOK—a shared body of knowledge for navigating the intersection of artificial intelligence and education. The journey toward AI readiness is ongoing. With disciplined measurement, informed leadership, and collaborative research, Ontario's colleges—and the broader educational community—can help shape that future with purpose and precision.

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APPENDICIES

Appendix A:
Governance Prototype Data Sources of QS World Top 10 AI Universities (2024-2025)

University	Primary Source	Secondary AI-Policy Source	Type	Collection method (Chatbot version)
Massachusetts Institute of Technology	Home page	Guidance for use of Generative AI tools	Web	Build 180F
Carnegie Mellon University	Home page	AI at CMU	Web	Build 180F
University of California, Berkeley	Home page	AI in Teaching & Learning Overview	Web	Build 180F
University of Oxford	Home page	AI in teaching and assessment	Web	Build 180F
Harvard University	Home page	Initial guidelines for the use of Generative AI tools	Web	Build 180F
National University of Singapore	Home page	Policy for Use of AI in Teaching and Learning PDF	Web	Build 180F
ETH Zurich	Home page	AI in Teaching and Learning	Web	Build 180F
Nanyang Technological University	Home page	NTU Position on the Use of GenAI in Research	Web	Build 180F
University of Toronto	Home page	Artificial Intelligence	Web	Build 180F
Hong Kong University of Science and Technology	Home page	Policy for GenAI Integration in Teaching and Learning	Web	Build 180F

Appendix B:
Governance Full Data Sources of Ontario Colleges (2024-2025)

College	Primary Source	Secondary Source (AI-Policy Specific documents)	Type	Collection method (Chatbot version)
Algonquin	Home page	AI & Academic Integrity page	Web	ON-AI-G-Build-204J-FullSafe
Cambrian	Home page	Recommendations on AI & Academic Integrity PDF	Web	ON-AI-G-Build-204J-FullSafe
Canadore	Home page	SoTL 2025 Symposium page	Web	ON-AI-G-Build-204J-FullSafe
Centennial	Home page	Guide to Generative AI	Web	ON-AI-G-Build-204J-FullSafe
Boreal	Home page	d'arts appliqués et de technologie PDF	Web	ON-AI-G-Build-204J-FullSafe
Conestoga	Home page	Gen AI for Students	Web	ON-AI-G-Build-204J-FullSafe
Confederation	Home page	Declaration on the Use of AI	Web	ON-AI-G-Build-204J-FullSafe
Durham	Home page	Academic Integrity & Use of Gen AI	Web	ON-AI-G-Build-204J-FullSafe
Fanshawe	Home page	AI Academic Framework PDF	Web	ON-AI-G-Build-204J-FullSafe
Fleming	Home page	None available	Web	ON-AI-G-Build-204J-FullSafe
George Brown	Home page	What is Academic Integrity (Gen AI)?	Web	ON-AI-G-Build-204J-FullSafe
Georgian	Home page	Guiding principles for AI	Web	ON-AI-G-Build-204J-FullSafe
Humber	Home page	Statement on AI	Web	ON-AI-G-Build-204J-FullSafe
La Cite	Home page	None available	Web	ON-AI-G-Build-204J-FullSafe
Lambton	Home page	No public access page	Web	ON-AI-G-Build-204J-FullSafe
Loyalist	Home page	Copyright: Generative AI	Web	ON-AI-G-Build-204J-FullSafe
Mohawk	Home page	None available	Web	ON-AI-G-Build-204J-FullSafe
Niagara	Home page	Academic Integrity & AI Statement	Web	ON-AI-G-Build-204J-FullSafe
Northern	Home page	None available	Web	ON-AI-G-Build-204J-FullSafe

Sault	Home page	None available	Web	ON-AI-G-Build-204J-FullSafe
Seneca	Home page	Gen AI Policy	Web	ON-AI-G-Build-204J-FullSafe
Sheridan	Home page	Responsible Use of AI PDF	Web	ON-AI-G-Build-204J-FullSafe
St. Clair	Home page	Learning With Integrity	Web	ON-AI-G-Build-204J-FullSafe
St. Lawrence	Home page	None available	Web	ON-AI-G-Build-204J-FullSafe

Appendix C:
Utility Bot (Python) to Preload Rubrics to Memory for OpenAI API Calls

```
# Upload rubrics only

from openai import OpenAI
import os
from dotenv import load_dotenv

# === Load API Key ===
load_dotenv()
client = OpenAI(api_key=os.getenv("OPENAI_API_KEY"))

# === Upload Only ===
RUBRIC_FILENAME = "rubrics.txt"
OUTPUT_FILE = "rubric_file_id.txt"

file = client.files.create(
    file=open(RUBRIC_FILENAME, "rb"),
    purpose="assistants"
)

with open(OUTPUT_FILE, "w") as f:
    f.write(file.id)

print("✅ Rubric file uploaded successfully.")
print("🆔 File ID:", file.id)
print(f"💾 File ID saved to {OUTPUT_FILE}")
```

Appendix D:
Bench-Build-180F – AI Governance Benchmarking Bot

```
# 180F
import os
import re
import requests
import pandas as pd
import fitz  # PyMuPDF
from bs4 import BeautifulSoup
from docx import Document
from datetime import datetime
from openai import OpenAI

EXCEL_PATH = "Top 10 AI universities worldwide.xlsx"
TEMP_TXT = "temp.txt"
TEMP2_TXT = "temp2.txt"
PDF_PATH = "temp.pdf"
BUILD = "Build 180F"

now = datetime.now()
timestamp = now.strftime("%Y-%m-%d-%H-%M-%S")
DOCX_PATH = f"AI_Gov_{timestamp}.docx"

client = OpenAI()
HEADERS = {"User-Agent": "Mozilla/5.0"}

# Setup: clear or create log and output files
for path in [TEMP_TXT, TEMP2_TXT, DOCX_PATH]:
    if os.path.exists(path):
        os.remove(path)
open(TEMP_TXT, "w").close()
open(TEMP2_TXT, "w").close()

def extract_html(url):
    try:
        r = requests.get(url, headers=HEADERS, timeout=15)
        if r.status_code == 200:
            soup = BeautifulSoup(r.content, "html.parser")
            return soup.get_text(separator=" ", strip=True)[:4000]
    except Exception as e:
        return f"⚠️ HTML error: {str(e)}"
    return None

def extract_pdf(url):
    try:
        r = requests.get(url, headers=HEADERS, timeout=15)
        if r.status_code == 200:
            with open(PDF_PATH, "wb") as f:
```

```
- Independent AI Office, task force, or standing committee
- AI Literacy required or recommended
- AI used in Teaching & Learning
- AI used in administrative processes
- AI privacy/security policies in place

Clarity: (+2 each)
- Institution-wide AI policy
- Department-level AI policy support
- Guidelines for students
- Guidelines for staff
- Guidelines for contractors

Relevance (select one):
10 = Embraced, 8 = Encouraged, 6 = Deferred, 4 = Discouraged, 2 = Penalized, 0 = Prohibited
(Use odd numbers for mixed cases)

Transparency: (+2 each)
- Policy linked from homepage, or AI news/search present
- Policy page does not require login
- Policy in student handbook
- AI-detection tool usage guidance
- AI support contact (email/chatbot/hotline)

Practicality: (+2 each)
- Enforcement mechanisms
- AI-supportive infrastructure
- AI-enhanced tools permitted (e.g., Grammarly)
- GenAI tools available to students
- AI course offerings

Adj 1: (–3 to +3) Policy clarity, scope, enforceability
Adj 2: (–3 to +3) Institutional seriousness, oversight

Then total Raw Score and Adjusted Score. Explain each score.
"""
    messages = [
        {"role": "system", "content": "You are an expert in AI governance evaluation."},
        {"role": "user", "content": rubric + f"\n\nSnippet:\n{snippet}"}
    ]
    response = client.chat.completions.create(
        model="gpt-4",
        messages=messages,
        temperature=0.0,
        max_tokens=1200
    )
    return response.choices[0].message.content.strip()
```

```
def parse_scores(text):
    """Extract the numeric scores from the LLM's response text."""
    keys = ["Completeness", "Clarity", "Relevance", "Transparency", "Practicality", "Adj 1", "Adj 2",
"Raw Score", "Adjusted Score"]
    text = text.replace("/10", "")
    result = {}
    for key in keys:
        match = re.search(rf"{key}[:\s]*([+-]?\d+)", text)
        result[key] = int(match.group(1)) if match else 0
    return result

def style_table_grid(table):
    """Apply a grid style to the given table for visible borders."""
    table.style = 'Table Grid'

def add_rubric_tables(doc):
    """Append scoring rubric tables as an appendix to the Word document."""
    doc.add_page_break()
    doc.add_heading("Appendix: Scoring Rubrics", level=1)

    def add_table(title, rows):
        doc.add_heading(title, level=2)
        t = doc.add_table(rows=1, cols=2)
        style_table_grid(t)
        hdr = t.rows[0].cells
        hdr[0].text = "Score"
        hdr[1].text = "Criteria"
        for score, desc in rows:
            row = t.add_row().cells
            row[0].text = score
            row[1].text = desc

    add_table("Completeness Rubric", [
        ("+2", "Independent AI Office, task force, or committee"),
        ("+2", "AI Literacy required or recommended"),
        ("+2", "AI used in Teaching & Learning"),
        ("+2", "AI used in admin processes"),
        ("+2", "Privacy/security policies in place")
    ])
    add_table("Clarity Rubric", [
        ("+2", "Institution-wide AI policy from leadership"),
        ("+2", "Department-level policies support institutional policy"),
        ("+2", "Guidelines for students"),
        ("+2", "Guidelines for staff"),
        ("+2", "Guidelines for contractors/suppliers")
    ])
    add_table("Relevance Rubric", [
        ("10", "Embraced"), ("8", "Encouraged"), ("6", "Deferred"),
        ("4", "Discouraged"), ("2", "Penalized"), ("0", "Prohibited")
    ])
```

```
    add_table("Transparency Rubric", [
        ("+2", "Policy linked from homepage or AI visible"),
        ("+2", "Policy accessible without login"),
        ("+2", "Included in student handbook"),
        ("+2", "Mentions AI-detection tools"),
        ("+2", "AI help: chatbot/email/hotline")
    ])
    add_table("Practicality Rubric", [
        ("+2", "Enforcement mechanisms"),
        ("+2", "AI-supportive infrastructure"),
        ("+2", "AI-assisted tools allowed"),
        ("+2", "GenAI tools for students"),
        ("+2", "AI course offerings")
    ])
    add_table("Adjustment Rubric: Adj 1 – Content", [
        ("+3", "Innovative, enforceable, comprehensive"),
        ("+2", "Clear and aligned with goals"),
        ("+1", "Good but lacks specifics"),
        ("0", "Neutral"),
        ("–1", "Ambiguous or fragmented"),
        ("–2", "Weak enforcement or vague"),
        ("–3", "Superficial or boilerplate")
    ])
    add_table("Adjustment Rubric: Adj 2 – Institutional Posture", [
        ("+3", "Independent oversight committee"),
        ("+2", "Internal review group"),
        ("+1", "Annual review built-in"),
        ("0", "No evidence"),
        ("–1", "Fragmented or instructor-led"),
        ("–2", "Relies on external associations"),
        ("–3", "Defers to government without internal ownership")
    ])

def main():
    # Load data from Excel
    df = pd.read_excel(EXCEL_PATH)
    urls = dict(zip(df["Institution"], df["Policy URL"]))

    # Create Word document and add header information
    doc = Document()
    doc.add_heading("AI Governance Policy Evaluation", 0)
    doc.add_paragraph(f"Generated using Governance Chatbot | Capstone – Ontario Tech | {BUILD}")
    doc.add_paragraph(f"Date: {now.strftime('%B %d, %Y %H:%M:%S')}")

    results = []
    # Process each university in the dataset
    for uni, url in urls.items():
        print(f"Processing {uni}...")
```

```
        print(f"Fetching policy snippet for {uni}...")
        snippet = get_snippet(url)
        print("Snippet extraction complete.")

        # Evaluate snippet using LLM
        print(f"Sending snippet to OpenAI for evaluation...")
        result = evaluate_with_llm(snippet, uni)
        print("LLM evaluation complete.")

        # Log the LLM's evaluation result
        with open(TEMP2_TXT, "a", encoding="utf-8") as f:
            f.write(f"{uni}\n{result}\n\n")

        # Write result and scores to the Word document
        doc.add_heading(f"{uni}", level=1)
        doc.add_paragraph(result)

        # Parse numeric scores and store results
        scores = parse_scores(result)
        results.append((uni, scores))
        print(f"Results recorded for {uni}.\n")

    # Create summary table sorted by final Adjusted Score
    doc.add_heading("Summary Grid", level=1)
    table = doc.add_table(rows=1, cols=10)
    style_table_grid(table)
    headers = ["Inst.", "Comp", "Clarity", "Rel", "Transp", "Pract", "Adj1", "Adj2", "Raw", "Final"]
    for i, header in enumerate(headers):
        table.cell(0, i).text = header

    for uni, score_dict in sorted(results, key=lambda x: x[1]["Adjusted Score"], reverse=True):
        row_cells = table.add_row().cells
        row_cells[0].text = uni
        row_cells[1].text = str(score_dict["Completeness"])
        row_cells[2].text = str(score_dict["Clarity"])
        row_cells[3].text = str(score_dict["Relevance"])
        row_cells[4].text = str(score_dict["Transparency"])
        row_cells[5].text = str(score_dict["Practicality"])
        row_cells[6].text = str(score_dict["Adj 1"])
        row_cells[7].text = str(score_dict["Adj 2"])
        row_cells[8].text = str(score_dict["Raw Score"])
        row_cells[9].text = str(score_dict["Adjusted Score"])

    # Append detailed scoring rubrics tables
    add_rubric_tables(doc)
    # Save the Word document
    doc.save(DOCX_PATH)
    print(f"✅ Build {BUILD} complete. Output: {DOCX_PATH}")

if __name__ == "__main__":
    main()
```

Appendix E:
Six-Sigma-Parser-1– Analytic Stability Testing Bot

```
# Six-Sigma-Parser-1.py
# Parses multiple AI_Gov_*.docx reports to extract Summary Grid data
# Computes per-institution Std Dev on 'Final' scores across runs
# Adds summary row of column-wise averages

import os
import re
import pandas as pd
from docx import Document
from collections import defaultdict

# === Configuration ===
CRITERIA = ["Comp", "Clarity", "Rel", "Transp", "Pract", "Adj1", "Adj2", "Raw", "Final"]

def parse_summary_table(doc):
    table_data = []
    for table in doc.tables:
        first_cell = table.cell(0, 0).text.strip()
        if "Summary Grid" in first_cell or first_cell == "Inst.":
            for row in table.rows[1:]:
                values = [cell.text.strip() for cell in row.cells]
                if len(values) >= 10:
                    table_data.append(values)
    return table_data

def parse_all_reports():
    run_data = defaultdict(list)
    all_institutions = set()

    for fname in sorted(f for f in os.listdir() if f.startswith("AI_Gov_") and f.endswith(".docx")):
        print(f"Parsing {fname}...")
        doc = Document(fname)
        data = parse_summary_table(doc)
        run_id = fname.replace("AI_Gov_", "").replace(".docx", "")

        for row in data:
            inst = row[0]
            all_institutions.add(inst)
            try:
                scores = [int(val) for val in row[1:10]]
                run_data[inst].append((run_id, *scores))
            except ValueError:
                continue

    rows = []
    for inst in sorted(all_institutions):
        if inst not in run_data:
            continue
        for entry in run_data[inst]:
```

```
        run_id, *scores = entry
        rows.append([run_id, inst] + scores)

    df = pd.DataFrame(rows, columns=["Run", "Institution"] + CRITERIA)

    # === Compute Std Dev by Institution ===
    stddev_df = df.groupby("Institution")["Final"].std().reset_index().rename(columns={"Final": "Std
Dev"})
    df = df.merge(stddev_df, on="Institution", how="left")

    # === Add Summary Row ===
    summary_row = ["AVG", "- Avg -"] + [round(df[col].mean(), 2) for col in CRITERIA] + [round(df["Std
Dev"].mean(), 2)]
    df.loc[len(df.index)] = summary_row

    df.to_csv("AI_Gov_RR_Parsed.csv", index=False)
    print("\n✅ Saved to AI_Gov_RR_Parsed.csv")

if __name__ == "__main__":
    parse_all_reports()
```

Appendix F:
Six-Sigma-Monte-Carlo-4 – Predictive Modeling Bot

```
# Six-Sigma-MonteCarlo-4.py
# Performs Monte Carlo simulation on Final scores from AI_Gov_RR_Parsed.csv
# Uses 1,000,000 simulations to compute DPMO, Sigma value, and Sigma level per institution
# Assumes defect is outside tolerance of ±7 from the average Final score

import pandas as pd
import numpy as np
from scipy.stats import norm

# Constants
NUM_SIMULATIONS = 1_000_000
TOLERANCE = 7
SIGMA_THRESHOLDS = [
    (0, 691462, 1),
    (691463, 308538, 2),
    (308539, 66807, 3),
    (66808, 6210, 4),
    (6211, 233, 5),
    (234, 0, 6)
]

# Load data
input_file = "AI_Gov_RR_Parsed.csv"
df = pd.read_csv(input_file)

# Group by institution and collect all Final scores
grouped = df.groupby("Institution")

results = []

for inst, group in grouped:
    final_scores = group["Final"].dropna().values
    if len(final_scores) < 2:
        continue

    mean_score = np.mean(final_scores)
    std_dev = np.std(final_scores, ddof=1)

    # Simulate Final scores
    simulated = np.random.normal(mean_score, std_dev, NUM_SIMULATIONS)
    lower = mean_score - TOLERANCE
    upper = mean_score + TOLERANCE

    defects = np.sum((simulated < lower) | (simulated > upper))
    dpmo = (defects / NUM_SIMULATIONS) * 1_000_000

    # Compute sigma value using Z-score for yield
    yield_percent = 1 - (dpmo / 1_000_000)
    if yield_percent <= 0:
```

```
        sigma_value = 0
    else:
        sigma_value = round(norm.ppf(yield_percent) + 1.5, 2)

    # Determine integer sigma level
    sigma_level = int(np.floor(sigma_value)) if sigma_value < 6 else 6

    results.append({
        "Institution": inst,
        "Avg Final": round(mean_score, 2),
        "Std Dev": round(std_dev, 2),
        "DPMO": int(round(dpmo)),
        "Sigma Value": sigma_value,
        "Sigma Level": sigma_level
    })

# Save to CSV
df_out = pd.DataFrame(results)
outfile = "AI_Gov_MonteCarlo_Summary.csv"
df_out.to_csv(outfile, index=False)
print(f"\n✅ Monte Carlo analysis complete. Results saved to: {outfile}")
```

Appendix G:
Final Score Range, Mode, Sigma Tier and Best-Matched Report Run Date and Time – QS Top 10

Institution	Final Score Range	Mode Final Score	Sigma Tier	Best Matched Run Date and Time
Harvard University	43-45	45	6σ	2025-03-24-23-49-26
University of Toronto	41-47	43	5σ	2025-03-24-23-49-26
Carnegie Mellon University	37-43	39	4σ	2025-03-24-23-49-26
ETH Zurich	33-40	36	6σ	2025-03-24-23-49-26
University of California, Berkeley	35-40	36	5σ	2025-03-24-23-49-26
Massachusetts Institute of Technology	31-36	35	6σ	2025-03-24-23-49-26
Nanyang Technological University	22-36	35	3 σ	2025-03-24-23-49-26
National University of Singapore	33-34	34	6σ	2025-03-24-23-49-26
University of Oxford	33-41	34	4σ	2025-03-24-23-54-10
Hong Kong University of Science and Technology	24-35	33	3σ	2025-03-24-23-54-10

Appendix H:
Governance Institutional Summary and Explanation Based On Mode-Aligned Final Score–QS Top 10

Institution	Completeness	Clarity	Relevance	Transparency	Practicality	Adj1	Adj2	Raw	Final	Explanation
Harvard University	8	8	10	6	8	2	3	40	45	The AI governance policy of Harvard University is quite comprehensive and clear, covering a wide range of AI uses and issues. It shows a strong commitment to AI governance, with a dedicated Information Security and Data Privacy office and a range of approved AI tools. However, there are some areas where the policy could be improved, such as including an independent AI office or task force, requiring or recommending AI literacy, and providing guidelines for contractors. The policy could also be more transparent, with links from the homepage and inclusion in the student handbook.
University of Toronto	8	6	10	6	8	2	3	38	43	The University of Toronto's AI governance policy is quite comprehensive, with a clear focus on AI literacy, the use of AI in teaching and learning, and the establishment of an AI task force. However, there is room for improvement in terms of clarity, particularly at the department level and for contractors. The policy is highly relevant, as the university embraces the use of AI. Transparency could be improved by including the policy in the student handbook and providing guidance on AI-detection tool usage. The policy is practical, with enforcement mechanisms, supportive infrastructure, and

										permission for AI-enhanced tools. The university also offers GenAI tools to students. The policy is clear and has a wide scope, and the university shows a high level of seriousness and oversight in its AI governance.
Carnegie Mellon University	8	6	10	4	8	1	2	36	39	The AI governance policy at CMU is quite comprehensive, with a strong focus on the use of AI in teaching and learning, and the provision of AI tools and resources. However, there are some areas where the policy could be improved. For example, there is no mention of an independent AI office or task force, and it's not clear whether AI literacy is a requirement. The policy also lacks clarity in some areas, such as institution-wide AI policy and guidelines for contractors. The policy is highly relevant, as AI is embraced at CMU. However, transparency could be improved, as the policy page does not require login and there is no mention of AI-detection tool usage guidance. The policy is practical, with AI-supportive infrastructure, AI-enhanced tools, GenAI tools, and AI course offerings. The policy is somewhat clear and has a broad scope, but enforceability is not mentioned. The institution seems serious about AI and there is some level of oversight.
University of California, Berkeley	6	6	8	6	6	2	2	32	36	The policy snippet from UC Berkeley shows a clear commitment to the use of AI in teaching and learning, with guidelines for students and staff, and an institution-wide AI policy. However, there is no mention of an independent AI office, task force, or standing committee, and it's unclear if AI is used in administrative processes. The

										policy is linked from the homepage and is in the student handbook, but there's no mention of an AI-detection tool usage guidance. The university has an AI-supportive infrastructure and allows AI-enhanced tools, but there's no mention of enforcement mechanisms or GenAI tools available to students. The policy is clear, enforceable, and shows institutional seriousness and oversight.
ETH Zurich	6	6	10	6	4	2	2	32	36	The policy is quite comprehensive and clear, with a strong emphasis on AI literacy and the responsible use of AI. However, it lacks details on enforcement mechanisms, AI-supportive infrastructure, and AI course offerings. The policy also does not mention any independent AI office or task force, and there are no specific guidelines for contractors. The institution seems serious about the use of AI, but oversight mechanisms are not mentioned.
Massachusetts Institute of Technology	6	6	8	6	6	1	2	32	35	The policy scores relatively well in terms of completeness, clarity, relevance, transparency, and practicality. However, there are areas for improvement, such as the lack of explicit AI privacy/security policies, institution-wide AI policy, guidelines for contractors, policy in student handbook, enforcement mechanisms, and AI course offerings. The adjusted score reflects the policy's relative clarity and the institution's seriousness about AI governance.
Nanyang Technological University	6	6	10	6	4	1	2	32	35	The policy snippet from NTU shows a clear position on the use of Generative AI in research, acknowledging its potential benefits and risks. However, it lacks details on many aspects of AI

										governance, such as the presence of an independent AI office, AI literacy requirements, AI usage in teaching and learning, and administrative processes. The policy also lacks clarity on department-level support, guidelines for students and contractors, and transparency in terms of policy accessibility and AI support contacts. Practicality is also limited, with no mention of enforcement mechanisms, AI-supportive infrastructure, availability of GenAI tools to students, or AI course offerings. The adjusted score reflects the clarity of the policy and the institution's seriousness about AI governance but also acknowledges the lack of comprehensive scope and oversight mechanisms.
National University of Singapore	6	6	10	4	4	2	2	30	34	The policy shows a clear commitment to the use of AI in teaching and learning, with a dedicated workgroup and guidelines for both students and staff. However, it lacks in several areas, including AI literacy, AI use in administrative processes, department-level AI policy support, and guidelines for contractors. The policy also lacks transparency in terms of accessibility from the homepage and inclusion in the student handbook. Practicality is also limited, with no mention of enforcement mechanisms, permission for AI-enhanced tools, or AI course offerings. The adjusted score reflects the policy's clarity and institutional seriousness, but also its lack of enforceability and oversight.
University of Oxford	6	6	10	4	4	2	3	30	34	The policy shows a strong commitment to the ethical use of AI in teaching and learning, and it

										provides guidelines for students and staff. However, it lacks details on several aspects, such as the use of AI in administrative processes, department-level AI policy support, and AI-enhanced tools. It also does not provide information on enforcement mechanisms, AI-supportive infrastructure, and AI course offerings. The policy could be improved by providing more details on these aspects and by making it more transparent and practical.
Hong Kong University of Science and Technology	6	6	8	4	6	1	2	30	33	The AI governance policy at HKUST shows a clear focus on the use of AI in teaching and learning, with guidelines for students and faculty members. However, there is a lack of transparency, as the policy page requires a login and there is no clear AI support contact. The policy also lacks completeness, as there is no mention of an independent AI office, AI literacy requirements, or AI use in administrative processes. The practicality of the policy is somewhat limited, with no mention of enforcement mechanisms or AI-supportive infrastructure. The adjusted score reflects these strengths and weaknesses.

Note: Each institutional summary included in Appendix H reflects the evaluation run with a final score matching the statistical mode from 50 deterministic assessments. The full set of chatbot-generated reports for all institutions is archived separately and available upon request for replication or audit purposes.

Appendix I:
Monte Carlo Simulation Outputs for Governance Model Validation – QS Top 10

Figure I.1
Histogram of Simulated Governance Scores (c = 1,000,000)

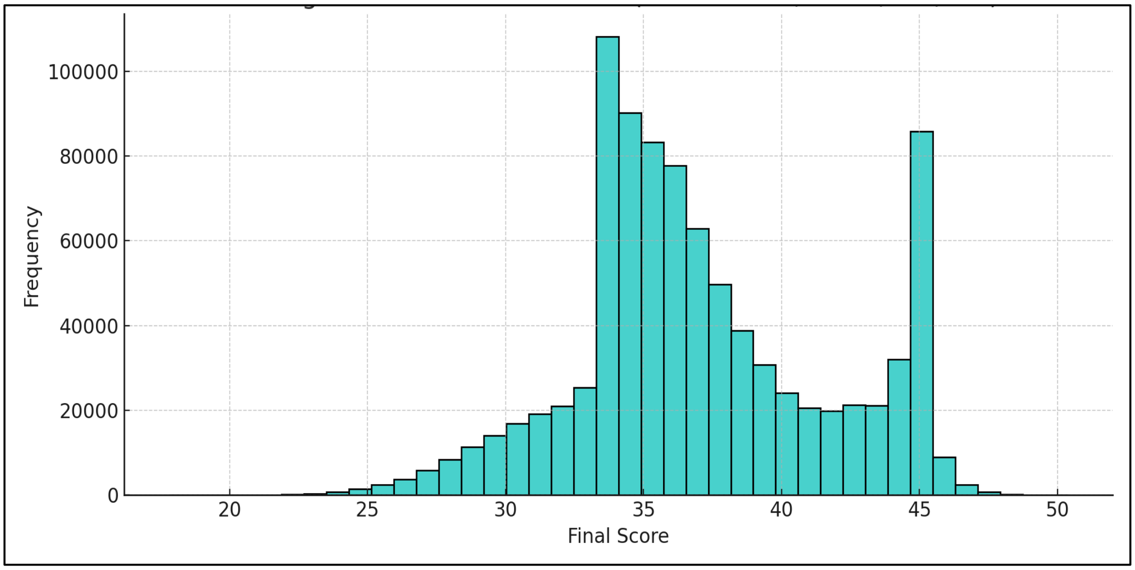
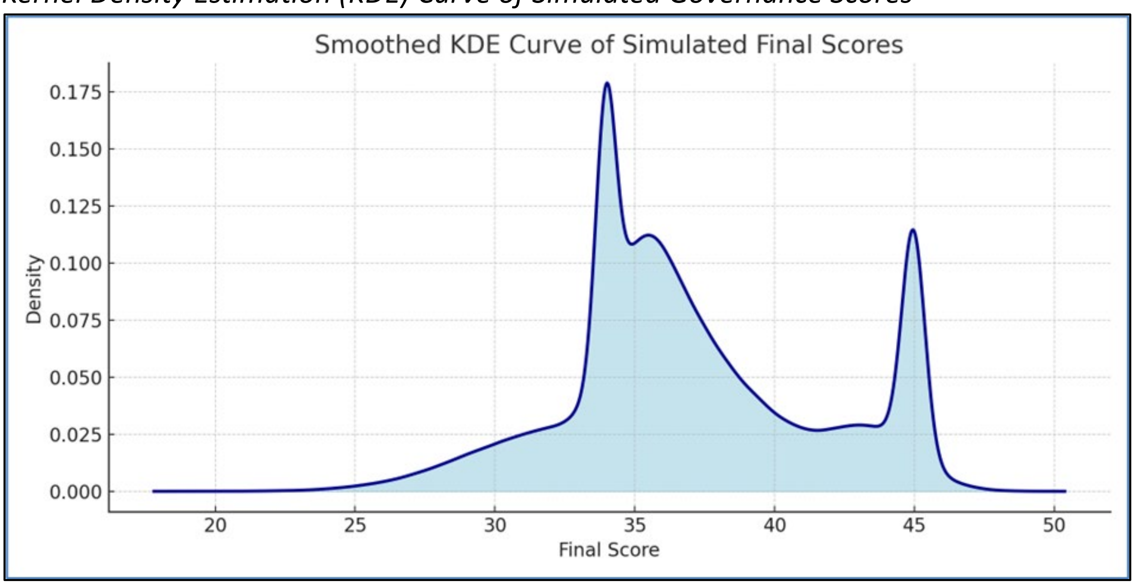


Figure I.1 is a histogram illustrating the frequency distribution of final governance scores across c = 1,000,000 simulated evaluation cycles. Each cycle introduced controlled variability across the five rubric pillars and two adjustment dimensions. The resulting distribution demonstrates convergence toward institution-specific means and supports the scoring model's repeatability under stochastic perturbation.

Figure I.2
Kernel Density Estimation (KDE) Curve of Simulated Governance Scores



The KDE curve presents a smoothed probability density function derived from the same c = 1,000,000 simulation events. This visualization reinforces the histogram's findings by revealing distributional characteristics such as modality, skewness, and dispersion. High-performing institutions exhibit tightly peaked KDE curves, indicating minimal variance and confirming governance evaluation stability consistent with Six Sigma reliability thresholds.

Interpretive Note on KDE Curve Twin Peaks. The appearance of two distinct peaks in the Kernel Density Estimation (KDE) curve reflects a bimodal distribution in the simulated governance scores across the QS Top 10 AI universities. This phenomenon arises from the underlying score heterogeneity among the institutions evaluated during the Monte Carlo simulation (c = 1,000,000).

The first peak, centered around 34/50, corresponds to institutions whose AI governance policies were moderately developed but exhibited variability in clarity, completeness, or accessibility. These institutions generated reproducible yet more dispersed scores across the five rubric pillars and two adjustment dimensions.

The second peak, located near 45/50, is attributable to a small subset of institutions—most notably Harvard University, the Massachusetts Institute of Technology (MIT), and the National University of Singapore (NUS). These institutions consistently produced high governance scores with minimal standard deviation (< 0.3) and were classified at the Six Sigma level during Gage R&R testing. Their sharply peaked, tightly clustered score distributions aggregated in the simulation to form a distinct secondary mode in the KDE.

This twin-peak structure is not an anomaly but rather a meaningful reflection of institutional maturity variation in AI governance. It confirms that the scoring model is sensitive enough to distinguish between high-performing institutions with structured, transparent AI policies and those with emerging or uneven governance practices.

Appendix J:
ON-AI-G-Build-204J-FullSafe – AI Governance Ontario Bot

```
# ON-AI-G-Build-204J-FullSafe
# First build to probe Ontario Colleges AI Governance
# Based on Bench-Build-180F survey of Top 10 AI universities worldwide


import os
import re
import requests
import pandas as pd
import fitz  # PyMuPDF
from bs4 import BeautifulSoup
from docx import Document
from datetime import datetime
from openai import OpenAI

EXCEL_PATH = "Ontario-Colleges.xlsx"
TEMP_TXT = "temp.txt"
TEMP2_TXT = "temp2.txt"
PDF_PATH = "temp.pdf"
BUILD = os.path.basename(__file__).replace(".py", "")

now = datetime.now()
timestamp = now.strftime("%Y-%m-%d-%H-%M-%S")
DOCX_PATH = f"ON-AI_Gov_{timestamp}.docx"

client = OpenAI()
HEADERS = {"User-Agent": "Mozilla/5.0"}

# Setup: clear or create log and output files
for path in [TEMP_TXT, TEMP2_TXT, DOCX_PATH]:
    if os.path.exists(path):
        os.remove(path)
open(TEMP_TXT, "w").close()
open(TEMP2_TXT, "w").close()

def extract_html(url):
    try:
        r = requests.get(url, headers=HEADERS, timeout=15)
        if r.status_code == 200:
            soup = BeautifulSoup(r.content, 'html.parser')
            if 'georgiancollege.ca/ctlae/academic-integrity' in url:
                anchor = soup.find(id='guiding-principles-for-ai')
                if anchor:
                    section_text = []
                    for sibling in anchor.find_all_next():
                        if sibling.name and sibling.name.startswith('h'):
                            break
                        section_text.append(sibling.get_text(strip=True))
```

```
            return ' '.join(section_text)[:6000]
        return soup.get_text(separator=' ', strip=True)[:6000]
    except Exception as e:
        return f'⚠️ HTML error: {str(e)}'
    return None
def get_snippet(url):
    if ".pdf" in url.lower():
        snippet = extract_pdf(url)
        if snippet and "PDF parsed" in snippet:
            snippet = "[Diagnostic Note: This AI policy is only available as a downloadable PDF. This limits
public accessibility and discoverability, which affects transparency.]\n" + snippet
        return snippet
    else:
        return extract_html(url)

def extract_pdf(url):
    try:
        print(f"📥 Downloading PDF from: {url}")
        r = requests.get(url, headers=HEADERS, timeout=15)
        if r.status_code == 200:
            with open(PDF_PATH, "wb") as f:
                f.write(r.content)
            print("✅ Saved temp.pdf")
            if os.path.exists(PDF_PATH):
                with fitz.open(PDF_PATH) as pdf:
                    text = "\n".join(page.get_text() for page in pdf)
                    print(f"📄 PDF parsed with {{len(text)}} characters")
                    if len(text.strip()) < 50:
                        print("⚠️ PDF contains very little extractable text.")
                        return "[PDF parsed but no meaningful content extracted.]"
                    return text[:3000]
        else:
            print(f"❌ PDF download failed with status code {r.status_code}")
    except Exception as e:
        print(f"❌ PDF error: {str(e)}")
        return f"[PDF error: {str(e)}]"
    return "[PDF parsing failed]"


def homepage_mentions_ai(url):
    """Check if the homepage contains any mention of AI or links to the AI policy."""
    if not url:
        return False
    try:
        r = requests.get(url, headers=HEADERS, timeout=10)
        if r.status_code == 200:
            soup = BeautifulSoup(r.content, "html.parser")
            text = soup.get_text(separator=" ", strip=True)
            text_lower = text.lower()
            return bool(re.search(r"\bai\b", text_lower)) or ("artificial intelligence" in text_lower)
    except Exception:
```

```
        return False
    return False

def is_login_required(url):
    """Determine if accessing the policy URL requires login (not publicly accessible)."""
    try:
        r = requests.get(url, headers=HEADERS, timeout=15)
        if r.status_code in (401, 403):
            return True
        if r.status_code == 200:
            content = r.text.lower()
            login_markers = ["login", "log in", "sign in", "signin", "password", "username"]
            if any(marker in content for marker in login_markers):
                return True
        return False
    except Exception:
        return True


    # --- Contextual Governance Metadata Insertion (Build 201E) ---
    metadata_notes = []
    if policy_url.strip() == homepage_url.strip():
        metadata_notes.append("⚠️ No separate AI policy page found. The policy URL points to the main
homepage.")
    if "login" in policy_url.lower() or "authenticate" in policy_url.lower() or "login" in
homepage_text.lower() or "sign in" in homepage_text.lower():
        metadata_notes.append("⚠️ AI policy page appears to require login. Transparency may be
reduced unless alternate public access is confirmed.")
    if "refer to" in snippet.lower() and "another college" in snippet.lower():
        metadata_notes.append("⚠️ This college refers students to another institution’s policy instead of
publishing its own.")
    if "pdf" in policy_url.lower() and not ("ai" in homepage_text.lower() or "artificial intelligence" in
homepage_text.lower()):
        metadata_notes.append("⚠️ AI governance guidance is available only in a downloadable PDF, not
linked from the homepage.")
    if all(keyword not in homepage_text.lower() for keyword in ["ai", "artificial intelligence", "chatgpt"]):
        metadata_notes.append("⚠️ The homepage contains no mention of AI-related policies, programs,
or contact points.")
    if metadata_notes:
     snippet = "\\n".join(metadata_notes) + "\\n\\n" + snippet



    # --- Build 201K Login Transparency Scoring Fix ---
    if 'login' in policy_url.lower() or 'authenticate' in policy_url.lower() or 'login' in
homepage_text.lower() or 'sign in' in homepage_text.lower():
        metadata_notes.append('⚠️ Login form or restricted access detected. Transparency score = 0.')
        transparency_score = 0
        snippet = 'Transparency: 0 (Login required)\\n' + snippet
    else:
```

```
        metadata_notes.append('✅ No login detected. Transparency score = +2.')
        transparency_score = 2
        snippet = 'Transparency: +2 (No login required)\\n' + snippet

    # Write updated snippet to temp.txt
    with open('temp.txt', 'a', encoding='utf-8') as f:
        f.write(f'--- {college} ---\\n{snippet}\\n\\n')


    # --- Build 201L: Diagnostic Snippet Logging ---
    try:
        snippet = f"Transparency: {transparency_score} ({login_note})\\n" + snippet
        print(f"WRITING SNIPPET FOR {college}:\\n{snippet[:300]}...\\n")
        with open('temp.txt', 'a', encoding='utf-8') as f:
            f.write(f"--- {college} ---\\n{snippet}\\n\\n")
    except Exception as e:
        print(f"❌ Failed to write snippet for {college}: {e}")


    # --- Build 201M: Robust Snippet Logging and Fallback ---
    if not snippet.strip():
        snippet = '⚠️ No content parsed. Skipping scoring.'
        print(f'⚠️ Snippet is empty for {college}')
    else:
        snippet = f'Transparency: {transparency_score} ({login_note})\\n' + snippet
        print(f'🟢 Snippet prepared for {college}:\\n{snippet[:300]}...')

    try:
        with open('temp.txt', 'a', encoding='utf-8') as f:
            f.write(f"--- {college} ---\\n{snippet}\\n\\n")
        print(f'📝 Snippet written to temp.txt for {college}')
    except Exception as e:
        print(f"❌ Failed to write snippet for {college}: {e}")


    # --- Build 201N: Force Snippet Initialization and Logging ---
    snippet = snippet if 'snippet' in locals() else ''
    if not snippet.strip():
        print(f'🛑 Empty snippet for {college}, nothing to evaluate')
    else:
        snippet = f'Transparency: {transparency_score} ({login_note})\\n' + snippet
        print(f'🟢 Snippet ready for {college}:\\n{snippet[:300]}...')

    try:
        with open('temp.txt', 'a', encoding='utf-8') as f:
            f.write(f"--- {college} ---\\n{snippet}\\n\\n")
        print(f'📝 Snippet written to temp.txt for {college}')
    except Exception as e:
        print(f"❌ Failed to write snippet for {college}: {e}")

def evaluate_with_llm(snippet, university):
```

```
    """Use OpenAI GPT-4 to evaluate the policy snippet against the scoring rubric."""
    rubric = f"""
Evaluate the AI governance policy snippet from {{university}}. Use the rubric below to score.

Each Governance pillar is scored out of 10. Unless otherwise stated, award +2 per met condition.

Completeness: (+2 each)
- Independent AI Office, task force, or standing committee
- AI Literacy required or recommended
- AI used in Teaching & Learning
- AI used in administrative processes
- AI privacy/security policies in place

Clarity: (+2 each)
- Institution-wide AI policy
- Department-level AI policy support
- Guidelines for students
- Guidelines for staff
- Guidelines for contractors

Relevance (select one):
10 = Embraced, 8 = Encouraged, 6 = Deferred, 4 = Discouraged, 2 = Penalized, 0 = Prohibited
(Use odd numbers for mixed cases)

Transparency: (+2 each)
- Policy linked from homepage, or AI news/search present
- Policy page does not require login
- Policy in student handbook
- AI-detection tool usage guidance
- AI support contact (email/chatbot/hotline)

Practicality: (+2 each)
- Enforcement mechanisms
- AI-supportive infrastructure
- AI-enhanced tools permitted (e.g., Grammarly)
- GenAI tools available to students
- AI course offerings

Adj 1: (–3 to +3) Policy clarity, scope, enforceability
Adj 2: (–3 to +3) Institutional seriousness, oversight

Then total Raw Score and Adjusted Score. Explain each score.
"""
    messages = [
        {"role": "system", "content": "You are an expert in AI governance evaluation."},
        {"role": "user", "content": rubric + f"\\n\\nSnippet:\\n{snippet}"}
    ]
    response = client.chat.completions.create(
        model="gpt-4",
        messages=messages,
        temperature=0.0,
        max_tokens=1200
```

```
    )
    return response.choices[0].message.content.strip()

def parse_scores(text):
    """Extract the numeric scores from the LLM's response text."""
    keys = ["Completeness", "Clarity", "Relevance", "Transparency", "Practicality", "Adj 1", "Adj 2", "Raw 
Score", "Adjusted Score"]
    text = text.replace("/10", "")
    result = {}
    for key in keys:
        match = re.search(rf"{key}[:\s]*([+-]?\d+)", text)
        result[key] = int(match.group(1)) if match else 0
    return result

def style_table_grid(table):
    """Apply a grid style to the given table for visible borders."""
    table.style = 'Table Grid'

def add_rubric_tables(doc):
    """Append scoring rubric tables as an appendix to the Word document."""
    doc.add_page_break()
    doc.add_heading("Appendix: Scoring Rubrics", level=1)

    def add_table(title, rows):
        doc.add_heading(title, level=2)
        t = doc.add_table(rows=1, cols=2)
        style_table_grid(t)
        hdr = t.rows[0].cells
        hdr[0].text = "Score"
        hdr[1].text = "Criteria"
        for score, desc in rows:
            row = t.add_row().cells
            row[0].text = score
            row[1].text = desc

    add_table("Completeness Rubric", [
        ("+2", "Independent AI Office, task force, or committee"),
        ("+2", "AI Literacy required or recommended"),
        ("+2", "AI used in Teaching & Learning"),
        ("+2", "AI used in admin processes"),
        ("+2", "Privacy/security policies in place")
    ])
    add_table("Clarity Rubric", [
        ("+2", "Institution-wide AI policy from leadership"),
        ("+2", "Department-level policies support institutional policy"),
        ("+2", "Guidelines for students"),
        ("+2", "Guidelines for staff"),
        ("+2", "Guidelines for contractors/suppliers")
    ])
    add_table("Relevance Rubric", [
        ("10", "Embraced"), ("8", "Encouraged"), ("6", "Deferred"),
        ("4", "Discouraged"), ("2", "Penalized"), ("0", "Prohibited")
```

```
    ])
    add_table("Transparency Rubric", [
        ("+2", "Policy linked from homepage or AI visible"),
        ("+2", "Policy accessible without login"),
        ("+2", "Included in student handbook"),
        ("+2", "Mentions AI-detection tools"),
        ("+2", "AI help: chatbot/email/hotline")
    ])
    add_table("Practicality Rubric", [
        ("+2", "Enforcement mechanisms"),
        ("+2", "AI-supportive infrastructure"),
        ("+2", "AI-assisted tools allowed"),
        ("+2", "GenAI tools for students"),
        ("+2", "AI course offerings")
    ])
    add_table("Adjustment Rubric: Adj 1 – Content", [
        ("+3", "Innovative, enforceable, comprehensive"),
        ("+2", "Clear and aligned with goals"),
        ("+1", "Good but lacks specifics"),
        ("0", "Neutral"),
        ("–1", "Ambiguous or fragmented"),
        ("–2", "Weak enforcement or vague"),
        ("–3", "Superficial or boilerplate")
    ])
    add_table("Adjustment Rubric: Adj 2 – Institutional Posture", [
        ("+3", "Independent oversight committee"),
        ("+2", "Internal review group"),
        ("+1", "Annual review built-in"),
        ("0", "No evidence"),
        ("–1", "Fragmented or instructor-led"),
        ("–2", "Relies on external associations"),
        ("–3", "Defers to government without internal ownership")
    ])

def main():
    # Load data from Excel
    df = pd.read_excel(EXCEL_PATH)
    urls = dict(zip(df["College"], df["Policy URL"]))

    # Create Word document and add header information
    doc = Document()
    doc.add_heading("AI Governance Policy Evaluation", 0)
    doc.add_paragraph(f"Generated using Governance Chatbot | Capstone – Ontario Tech | {BUILD}")
    doc.add_paragraph(f"Date: {now.strftime('%B %d, %Y %H:%M:%S')}")

    results = []
    # Process each university in the dataset
    for uni, url in urls.items():
        login_form_detected = False  # Default value unless found
        # --- Build 201R: Smarter login detection ---
        lower_html = html.lower() if 'html' in locals() else ''
```

```
    if any(term in lower_html for term in ['type="password"', 'login', '/login', 'sign in', 'signin', 'id="login-link"']):
      login_form_detected = True
      print(f'🔒 Login field detected for {uni}')
    else:
      login_form_detected = False
      print(f'🔓 No login field detected for {uni}')

    print(f"Processing {uni}...")
    print(f"Fetching policy snippet for {uni}...")
    snippet = get_snippet(url)
    print("Snippet extraction complete.")

    # Evaluate snippet using LLM
    print(f"Sending snippet to OpenAI for evaluation...")
    # --- Build 201O: Guaranteed snippet logging before OpenAI call ---
    try:
      if not snippet.strip():
        snippet = '⚠️ No content parsed or available for this institution.'
        print(f'🛑 Snippet is empty for {uni}')
      else:
        print(f'🟢 Snippet ready for {uni}:\\n{snippet[:300]}...')
      with open(TEMP_TXT, 'a', encoding='utf-8') as tempfile:
        tempfile.write(f"--- {uni} ---\\n{snippet}\\n\\n")
      print(f'📝 Snippet written to temp.txt for {uni}')
    except Exception as err:
      print(f'❌ Error writing snippet to temp.txt for {uni}: {err}')

    # --- Build 201P: Keyword-aligned snippet extraction ---
    keyword_list = [
      'artificial intelligence', 'ai governance', 'ai use',
      'ai policy', 'generative ai', 'genai', 'machine learning'
    ]
    if not snippet:
      print(f"🛑 Snippet is None or empty for {uni}, skipping.")
      continue
    text_lower = full_text.lower() if 'full_text' in locals() else snippet.lower()
    match_indices = [text_lower.find(k) for k in keyword_list if k in text_lower]
    start_index = min(match_indices) if match_indices else 0
    snippet_start = max(start_index - 100, 0)
    snippet = full_text[snippet_start:snippet_start + 3000] if 'full_text' in locals() else snippet[:3000]
    print(f'🔍 Snippet aligned from index {snippet_start}')

    # --- Build 201Q: Insert metadata note for login status ---
    login_msg = (
      '[Metadata Note: A login prompt was detected. The AI policy may not be publicly accessible.]'
      if login_form_detected
      else '[Metadata Note: No login prompt was detected. The AI policy page is publicly accessible.]'
    )
    snippet = login_msg + '\\n' + snippet
    print(f'📌 Injected login note for {uni}: {login_msg}')
```

```
    # --- Build 201S: Ensure metadata note is prepended into OpenAI snippet ---
    snippet = f"[Metadata Note: {'No login prompt was detected.' if not login_form_detected else 'A
login prompt was detected. The AI policy may not be publicly accessible.'}]\\n\\n" + snippet
    result = evaluate_with_llm(snippet, uni)
    print("LLM evaluation complete.")

    # Log the LLM's evaluation result
    with open(TEMP2_TXT, "a", encoding="utf-8") as f:
      f.write(f"{uni}\\n{result}\\n\\n")

    # Write result and scores to the Word document
    doc.add_heading(f"{uni}", level=1)
    doc.add_paragraph(result)

    # Parse numeric scores and store results
    scores = parse_scores(result)
    results.append((uni, scores))
    print(f"Results recorded for {uni}.\\n")

  # Create summary table sorted by final Adjusted Score
  doc.add_heading("Summary Grid", level=1)
  table = doc.add_table(rows=1, cols=10)
  style_table_grid(table)
  headers = ["Inst.", "Comp", "Clarity", "Rel", "Transp", "Pract", "Adj1", "Adj2", "Raw", "Final"]
  for i, header in enumerate(headers):
    table.cell(0, i).text = header

  for uni, score_dict in sorted(results, key=lambda x: x[1]["Adjusted Score"], reverse=True):
    row_cells = table.add_row().cells
    row_cells[0].text = uni
    row_cells[1].text = str(score_dict["Completeness"])
    row_cells[2].text = str(score_dict["Clarity"])
    row_cells[3].text = str(score_dict["Relevance"])
    row_cells[4].text = str(score_dict["Transparency"])
    row_cells[5].text = str(score_dict["Practicality"])
    row_cells[6].text = str(score_dict["Adj 1"])
    row_cells[7].text = str(score_dict["Adj 2"])
    row_cells[8].text = str(score_dict["Raw Score"])
    row_cells[9].text = str(score_dict["Adjusted Score"])

  # Append detailed scoring rubrics tables
  add_rubric_tables(doc)
  # Save the Word document
  doc.save(DOCX_PATH)
  print(f"✅ Build {BUILD} complete. Output: {DOCX_PATH}")

if __name__ == "__main__":
  main()
```

Appendix K:
Final Score Range, Mode, Sigma Tier and Best-Matched Report Run Date and Time – Ontario 24

Institution	Governance Score Range	Mode Governance Score	Sigma Tier	Frequency	Best Matched Report Run Date and Time
Sheridan	37—43	43	5σ	22/50	2025-04-21-21-52-14
Fanshawe	37—43	41	4σ	26/50	2025-04-21-21-37-57
Conestoga	30—42	37	5σ	38/50	2025-04-21-21-37-57
Algonquin	33—44	35	4σ	29/50	2025-04-21-21-44-43
Humber	30—43	33	3σ	21/50	2025-04-21-21-37-57
Centennial	30—37	37	3σ	26/50	2025-04-21-21-37-57
Seneca	33—37	35	6σ	39/50	2025-04-21-21-37-57
Durham	32—42	33	4σ	33/50	2025-04-21-21-37-57
Niagara	0—40	34	3σ	27/50	2025-04-21-21-37-57
Loyalist	30—35	33	6σ	31/50	2025-04-21-21-37-57
George Brown	31—33	33	6σ	44/50	2025-04-21-21-37-57
Georgian	26—35	33	5σ	22/50	2025-04-21-22-11-30
Cambrian	29—38	31	6σ	31/50	2025-04-21-21-37-57
Canadore	0—30	28	3σ	25/50	2025-04-21-21-37-57
St. Clair	16—28	28	3σ	29/50	2025-04-21-22-05-31
Confederation	2—17	12	2σ	12/50	2025-04-21-22-05-31
Lambton	-4—8	2	0	15/50	2025-04-21-21-44-43
Fleming	0—0	0	0	50/50	2025-04-21-21-37-57
Boreal	-4—0	0	0	41/50	2025-04-21-21-37-57
La Cite	-4—0	0	0	26/50	2025-04-21-21-37-57
Mohawk	-4—0	0	0	27/50	2025-04-21-21-52-14
Sault	-4—2	-4	0	29/50	2025-04-21-21-58-13
St. Lawrence	-4—2	-4	0	46/50	2025-04-21-21-44-43
Northern	-4—4	-4	0	48/50	2025-04-21-21-37-57

Appendix L:
Governance Institutional Summary and Explanation Based On Mode-Aligned Final Score–Ontario 24

Institution	Completenes	Clarity	Relevance	Transparency	Practicality	Adj1	Adj2	Raw	Final	Explanation
Sheridan	8	8	10	6	6	2	3	38	43	The policy from Sheridan College shows a strong commitment to the responsible use of AI in teaching, learning, and administrative processes. It is clear and comprehensive, covering a wide range of issues related to AI, including privacy and security. However, there are some areas where the policy could be improved. For example, it does not mention an independent AI office or task force, and there is no explicit requirement for AI literacy. The policy also lacks clear enforcement mechanisms and does not provide guidelines for contractors. Despite these shortcomings, the policy demonstrates a high level of institutional seriousness and oversight, earning it a high adjusted score.
Fanshawe	8	6	10	6	6	2	3	36	41	The AI governance policy of the college is quite comprehensive, covering most areas of AI usage in academia. It shows a strong commitment to AI literacy, ethical use, and privacy/security considerations. However, it lacks specific enforcement

										mechanisms and does not mention AI course offerings. The policy is clear and the college shows seriousness in its AI governance, but there is room for improvement in terms of completeness, clarity, and practicality.
Conestoga	6	6	8	8	6	1	2	34	37	The college has a decent AI governance policy, with clear guidelines for students and a focus on privacy and security. However, the policy could be improved by extending its scope to staff and contractors, and by providing more information about enforcement mechanisms and AI course offerings. The policy is also not very transparent, with no link from the homepage and no mention of its inclusion in the student handbook.
Algonquin	8	6	8	6	4	1	2	32	35	The AI governance policy of the college is fairly comprehensive and clear, with a focus on academic integrity and responsible use of AI. However, it lacks details on enforcement mechanisms, AI-supportive infrastructure, and AI course offerings. The policy also does not provide guidelines for staff and contractors, and there is no mention of an independent AI office or task force. The policy is publicly accessible, which is a positive aspect of transparency. However, it could be improved by linking it from the homepage and including it in the student handbook. The institution seems serious about AI governance, but could

										improve by providing more details on oversight mechanisms.
Humber	6	6	8	6	4	1	2	30	33	The policy is somewhat complete and clear, with a focus on AI in teaching and learning, and guidelines for students. It is relevant, encouraging the use of AI. The policy is somewhat transparent, with a publicly accessible policy page and a link from the homepage. However, it lacks in practicality, with no mention of enforcement mechanisms, AI-supportive infrastructure, or AI course offerings. The adjustments reflect the policy's clarity and the institution's seriousness about AI, but also the lack of enforceability and oversight mechanisms.
Centennial	6	6	8	8	6	1	2	34	37	The policy is fairly comprehensive and clear, with a focus on student learning and academic integrity. However, it lacks details about AI use in administrative processes, privacy/security policies, and enforcement mechanisms. It also doesn't provide guidelines for staff and contractors, or mention AI course offerings. The policy is transparent and practical, but could benefit from more links and support contacts. The institution seems serious about AI, but could improve its oversight.
Seneca	6	8	8	6	4	1	2	32	35	The policy is clear and relevant, but lacks completeness in terms of AI literacy, AI use in teaching

										and learning, and the presence of an independent AI office. The policy is transparent in terms of accessibility, but lacks information on AI detection tools and AI support contact. Practicality is also limited, with no mention of enforcement mechanisms, AI-supportive infrastructure, or AI course offerings. The adjustments reflect the clarity of the policy and the institution's seriousness about AI, but also the lack of information on scope, enforceability, and oversight.
Durham	6	6	8	6	4	1	2	30	33	The policy shows a good start in terms of AI governance, with clear guidelines for students and staff, and a focus on academic integrity. However, it lacks in several areas, including AI literacy, AI use in administrative processes, and enforcement mechanisms. The institution also needs to improve transparency by linking the policy from the homepage and including it in the student handbook.
Niagara	6	6	8	6	4	2	2	30	34	The policy is fairly comprehensive and clear, with a focus on academic integrity. However, it lacks details on several aspects, such as the use of AI in administrative processes, department-level AI policy support, and guidelines for contractors. The policy also doesn't mention AI-supportive infrastructure, GenAI tools available to students, or AI course

										offerings. The policy is transparent and practical to some extent, but could be improved in these areas. The adjusted score reflects the policy's clarity, scope, and enforceability, as well as the institution's seriousness and oversight.
Loyalist	6	6	8	6	4	1	2	30	33	The policy provides some clarity and completeness, particularly around copyright considerations for AI. However, it lacks in areas such as enforcement mechanisms, AI-supportive infrastructure, and AI course offerings. The policy also does not clearly state whether there is an independent AI office or task force, and it does not provide guidelines for contractors. The institution seems serious about AI governance, but oversight is not clear.
George Brown	6	6	8	6	4	1	2	30	33	The policy snippet from George Brown College shows a moderate level of AI governance. While it does mention the use of AI in teaching and learning and has an institution-wide AI policy, it lacks explicit mention of an independent AI office, AI usage in administrative processes, and AI privacy/security policies. The policy is clear about its stance on AI usage and provides guidelines for students, but it does not provide guidelines for staff and contractors. The policy encourages the use of AI but with caution and responsibility. The policy page is publicly accessible,

										but there is no mention of the policy being linked from the homepage, in the student handbook, or AI support contact. The policy implies enforcement mechanisms and allows GenAI tools for students, but it does not mention AI-supportive infrastructure, AI-enhanced tools, or AI course offerings. The policy clarity is good, but the scope and enforceability are not explicitly stated. The institution seems serious about AI usage and its implications.
Georgian	6	6	10	6	2	1	2	30	33	The AI governance policy of Georgian College shows a clear commitment to AI and its ethical use in teaching and learning. However, the policy lacks explicit details about the infrastructure, enforcement mechanisms, and AI literacy requirements. The policy also does not mention any independent AI office or task force, and there are no clear guidelines for contractors. The policy is transparent in that it does not require a login to access, but it does not provide AI support contact or AI-detection tool usage guidance. The policy is practical in its commitment to AI course offerings, but it does not mention AI-supportive infrastructure or the permission of AI-enhanced tools. The policy's clarity and the institution's seriousness about AI are commendable, but the scope and oversight are not explicitly mentioned.

Cambrian	6	4	8	6	4	1	2	28	31	The college has a clear policy on AI governance, but it lacks in certain areas such as AI literacy, AI usage in teaching and learning, and department-level AI policy support. The policy is transparent and accessible, but it could be more prominently linked from the homepage. The university encourages the use of AI and provides GenAI tools and AI course offerings, but it could improve in terms of AI-supportive infrastructure and enforcement mechanisms. The policy is clear and the university shows seriousness in its approach to AI governance.
Canadore	6	4	8	6	4	-1	1	28	28	The college's AI governance policy is lacking in several areas. While it encourages the use of AI in teaching and learning, it does not provide clear guidelines for students, staff, or contractors. There is also no mention of an independent AI office, task force, or standing committee, and the policy does not address AI privacy or security. The policy is also not very transparent or practical, with no mention of enforcement mechanisms, AI-supportive infrastructure, or AI-enhanced tools. The policy's clarity, scope, and enforceability are also lacking, although the university does show some seriousness towards AI.
St. Clair	4	6	8	6	2	1	1	26	28	The policy is clear and accessible, but it lacks completeness, practicality, and transparency. It does not mention any AI office,

										task force, or committee, AI literacy, AI use in teaching and learning, AI use in administrative processes, or AI privacy/security policies. It also lacks department-level AI policy support, guidelines for staff and contractors, AI-detection tool usage guidance, AI support contact, enforcement mechanisms, AI-supportive infrastructure, AI-enhanced tools, GenAI tools, and AI course offerings. The policy encourages the use of AI but with integrity and honesty. The institution seems serious about AI integrity but lacks oversight details.
Confederation	4	2	6	4	2	-3	-3	18	12	The scores are low because the AI governance policy at the college is not comprehensive or clear. It lacks guidelines for different stakeholders, does not mention AI literacy, and does not have a clear enforcement mechanism. The policy also lacks transparency, as it is not linked from the homepage and does not provide AI support contact. The policy's practicality is also low, as it does not mention AI-supportive infrastructure or AI-enhanced tools. The adjustments are negative due to the lack of clarity, scope, and enforceability of the policy, as well as the lack of institutional seriousness and oversight.
Lambton	2	2	0	4	0	-3	-3	8	2	The snippet does not provide sufficient information about the AI governance policy at the

										college’s website available to the public. Most crucial information is only accessible with a college login. There is a lack of clarity and completeness in the policy, and the relevance, transparency, and practicality of the policy cannot be determined from the snippet. The adjusted score reflects the lack of clarity and institutional seriousness regarding AI governance.
Fleming	0	0	0	0	0	0	0	0	0	Based on the provided snippet, it's impossible to evaluate the AI governance policy of the college as the snippet does not contain any relevant information about the policy. The only information provided is that the AI policy page is publicly accessible, which would score +2 under the Transparency category. However, without further information about the policy's content, it's impossible to evaluate the policy under the categories of Completeness, Clarity, Relevance, Practicality, and the two adjustment categories.
Boreal	2	0	0	4	0	-3	-3	6	0	The raw score is low due to the lack of information about AI governance in the provided snippet. The adjusted score is zero due to the lack of clarity and institutional seriousness in AI governance. The college should consider developing a comprehensive AI

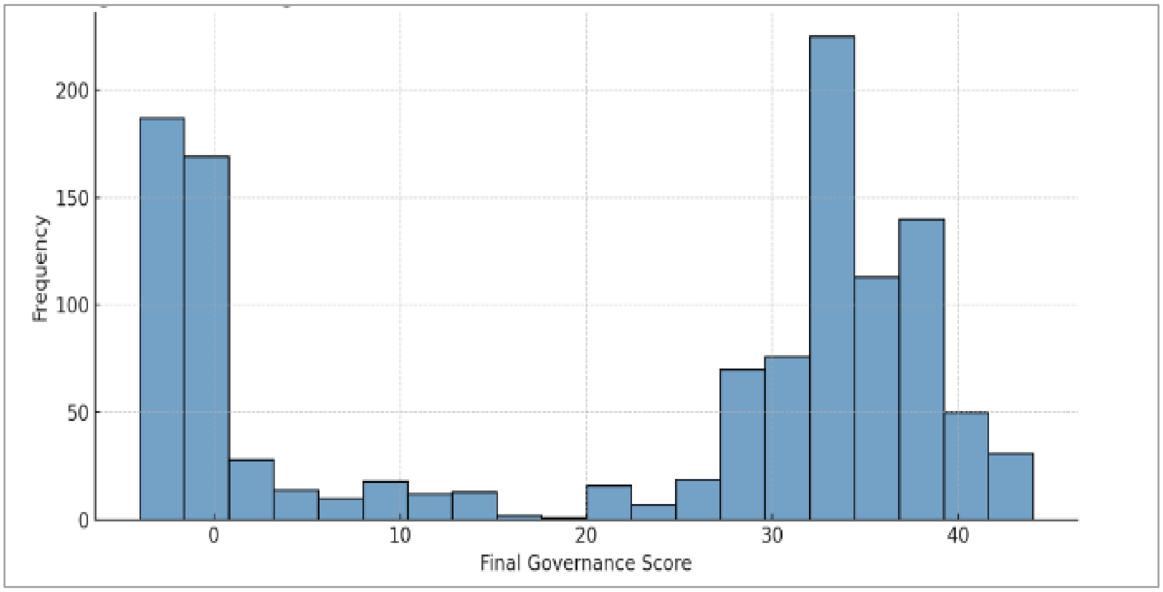
										governance policy that covers all aspects of AI usage, including teaching and learning, administrative processes, and privacy/security. The policy should also provide clear guidelines for students, staff, and contractors, and should be easily accessible and practical to implement.
Mohawk	0	0	0	0	0	0	0	0	0	Based on the provided snippet, it's difficult to evaluate the AI governance policy of the university as the snippet does not contain any specific information about AI governance. The snippet seems to be a general introduction or homepage of the college, not a specific policy or guideline related to AI governance. Therefore, without further information, it's impossible to score the college's AI governance policy based on the provided rubric.
La Cite	0	0	0	0	0	0	0	0	0	The provided snippet is in French and does not provide any specific information about AI governance at the college. It seems to be a general overview of the college's programs and services. Therefore, it's impossible to evaluate the AI governance policy based on this snippet.
Sault	0	0	0	2	0	-3	-3	2	-4	Based on the provided snippet, it's difficult to evaluate the AI governance policy of the college as the snippet does not contain any specific information about AI governance. The snippet seems to be a general

										introduction or overview of the university and its programs, but it does not mention anything about AI governance, AI literacy, AI usage in teaching and learning or administrative processes, AI privacy/security policies, institution-wide or department-level AI policies, guidelines for students, staff, or contractors, AI-detection tool usage guidance, AI support contact, enforcement mechanisms, AI-supportive infrastructure, AI-enhanced tools, or AI course offerings.
St. Lawrence	0	0	0	2	0	-3	-3	2	-4	Based on the provided snippet, it's difficult to evaluate the AI governance policy of the college, the snippet does not provide any specific information about AI governance. However, I will attempt to evaluate based on the limited information available. The scores are extremely low due to the lack of any mention of AI governance in the provided snippet. The college may have a comprehensive AI governance policy, but it is not reflected in the provided information.
Northern	0	0	0	2	0	-3	-3	2	-4	The scores are extremely low due to the lack of any mention of AI governance in the provided snippet. It's possible that the college has a comprehensive AI governance policy that wasn't included in the snippet. A more detailed review would require access to the full policy.

Note: All reports in this appendix are based on the best-matched deterministic run aligned to the modal Final score, as identified in Appendix J. They were extracted from the first of five scoring batches (10 runs per institution, total = 50).

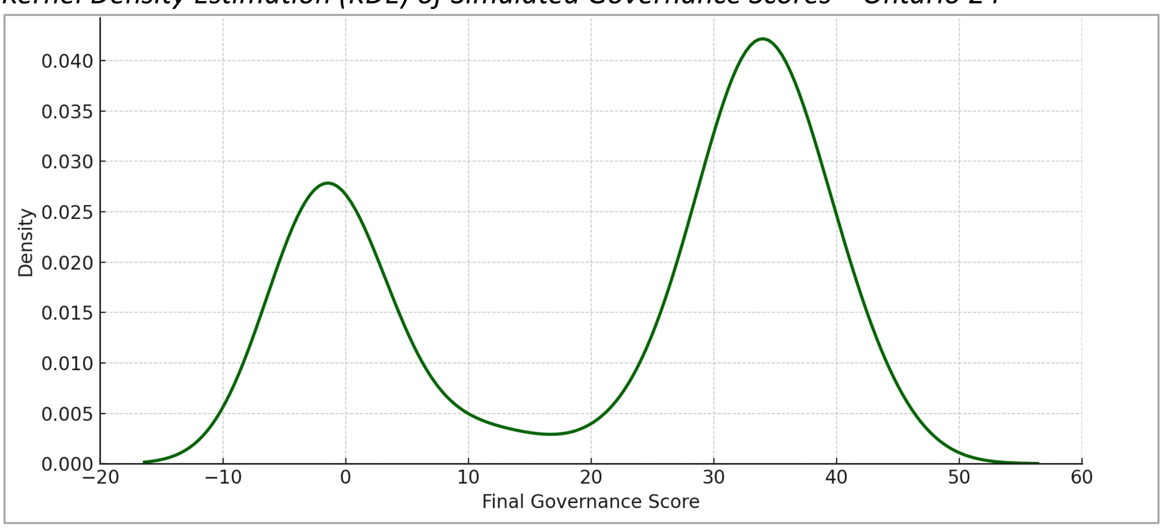
Appendix M:
Monte Carlo Simulation Outputs for Governance Model Validation – Ontario 24

Figure M.1
Histogram of Simulated Governance Scores (c = 1,000,000) – Ontario 24



This histogram illustrates the distribution of governance scores across one million evaluation cycles. It demonstrates convergence toward institution-specific mean values under controlled stochastic perturbation.

Figure M.2
Kernel Density Estimation (KDE) of Simulated Governance Scores – Ontario 24



The KDE curve reveals a unimodal, slightly right-skewed distribution of governance scores, reinforcing the model's statistical stability and reproducibility when applied to Ontario's publicly funded colleges.

Interpretive Note on KDE Curve Shape – Ontario 24 Colleges. The Kernel Density Estimation (KDE) curve in Figure M.2 exhibits a broad, asymmetrical distribution rather than the bimodal "twin-peak" structure observed in global benchmarks. This pattern reflects the greater **i**nstitutional convergence and compressed variability among Ontario's publicly funded community colleges with respect to AI governance maturity.

The absence of sharply defined peaks suggests that most institutions cluster near the **mid-tier of readiness**, with moderate governance scores exhibiting limited divergence. This is consistent with the sector's shared policy environment and uniform accountability structures—such as provincial funding frameworks, Strategic Mandate Agreements (SMAs), and common academic quality standards.

Nevertheless, the slight right ske**w** in the KDE curve indicates the presence of a subset of institutions that are beginning to differentiate themselves through more formalized AI governance strategies, clearer ethical guidelines, or transparent implementation mechanisms. While these higher-scoring colleges do not yet form a distinct second mode, their consistency and repeatability under simulation cycles suggest emerging leaders within the sector.

Overall, the KDE output confirms that the governance scoring model retains sufficient discriminatory sensitivity to detect performance gradations, while also accommodating sector-wide policy homogeneity. The simulation thus reinforces both the validity and reproducibility of the AI Transition Readiness Index (TRI) within the Ontario college context.

Appendix N:
CIP Codes Used to Identify AI-Relevant Programs in Ontario Colleges

Table N
39 AI-Relevant CIP Codes and Titles

CIP Code	Title
10.0304	Animation, interactive technology, video graphics and special effects
11.0101	Computer and information sciences, general
11.0102	Artificial intelligence
11.0103	Information technology
11.0104	Informatics
11.0199	Computer and information sciences and support services, general, other
11.0201	Computer programming/programmer, general
11.0202	Computer programming, specific applications
11.0301	Data processing and data processing technology/technician
11.0501	Computer systems analysis/analyst
11.0701	Computer science
11.0801	Web page, digital/multimedia and information resources design
11.0802	Data modelling/warehousing and database administration
11.0804	Modelling, virtual environments and simulation
11.0899	Computer software and media applications, other
11.0901	Computer systems networking and telecommunications, general
11.1001	Network and system administration/administrator
11.1002	System, networking and LAN/WAN management/manager
11.1003	Computer and information systems security/auditing/information assurance
11.1006	Computer support specialist
11.1099	Computer/information technology administration and management, other
11.9999	Computer and information sciences and support services, other
15.0305	Telecommunications technology/technician
15.0405	Robotics technology/technician
15.0406	Automation engineer technology/technician
15.1201	Computer engineering technology/technician, general
15.1202	Computer/computer systems technology/technician
15.1204	Computer software technology/technician
15.1299	Computer engineering technologies/technicians, other
30.1601	Accounting and computer science
45.0102	Research methodology and quantitative methods
47.0104	Computer installation and repair technology/technician
47.0614	Alternative fuel vehicle technology/technician
48.0510	CNC machinist technology/CNC machinist
51.2706	Medical informatics

52.0302	Accounting technology/technician and bookkeeping
52.1201	Management information systems, general
52.1206	Information resources management
52.1299	Management information systems and services, other

Appendix O:
GPLANET_P_L_Capstone.R (R script)

```
# GPLANET_P_L_Capstone.R
# Purpose: Evaluate AI Readiness using P (Programs) and L (Learners) metrics across Ontario Colleges
(2023–2024)


# --- Auto-Install and Load Required Packages ---
install_and_load <- function(pkg) {
  if (!requireNamespace(pkg, quietly = TRUE)) {
    install.packages(pkg, dependencies = TRUE)
  }
  library(pkg, character.only = TRUE)
}


install_and_load("readxl")
install_and_load("dplyr")
install_and_load("ggplot2")
install_and_load("tidyr")

options(dplyr.print_max = Inf)

# --- Set Working Directory ---
setwd("C:/Projects/HarvardX Capstone/HarvardX")
file_path <- "college_enrolment_headcount_2023-24.xlsx"

# --- Load 2023–2024 CIP Data ---
cip_data <- read_excel(file_path, sheet = "CIP") %>%
  filter(`Fiscal Year` == "2023-2024")

cip_data$`Headcount Full-Time Fall` <- as.numeric(cip_data$`Headcount Full-Time Fall`)

# --- AI-Relevant CIP Codes ---
ai_cips <- c(
  "10.0304", "11.0101", "11.0102", "11.0103", "11.0104", "11.0199",
  "11.0201", "11.0202", "11.0301", "11.0501", "11.0701", "11.0801",
  "11.0802", "11.0804", "11.0899", "11.0901", "11.1001", "11.1002",
  "11.1003", "11.1006", "11.1099", "11.9999", "15.0305", "15.0405",
  "15.0406", "15.1201", "15.1202", "15.1204", "15.1299", "30.1601",
  "45.0102", "47.0104", "47.0614", "48.0510", "51.2706", "52.0302",
  "52.1201", "52.1206", "52.1299"
)

# --- Filter and Summarize AI Programs ---
ai_programs <- cip_data %>%
  filter(`Instructional Program Class Code` %in% ai_cips)

ai_summary <- ai_programs %>%
```

```
  group_by(`College Name`) %>%
  summarise(
    P = n_distinct(`Instructional Program Class En Title`),
    L_Raw = sum(`Headcount Full-Time Fall`, na.rm = TRUE)
  )

# --- Total Enrollment by College ---
total_enrollment <- cip_data %>%
  group_by(`College Name`) %>%
  summarise(Total_Enrollment = sum(`Headcount Full-Time Fall`, na.rm = TRUE))

# --- Merge and Compute Share and Normalization ---
summary_grid <- merge(total_enrollment, ai_summary, by = "College Name", all.x = TRUE)
summary_grid[is.na(summary_grid)] <- 0

summary_grid <- summary_grid %>%
  mutate(
    L_Percent = (L_Raw / Total_Enrollment) * 100,
    L_Norm = (L_Percent - min(L_Percent)) / (max(L_Percent) - min(L_Percent))
  ) %>%
  select(`College Name`, P, L_Raw, Total_Enrollment, L_Percent, L_Norm)

# --- Plot 1: AI vs Total Programs ---

# Total programs per college
total_programs <- cip_data %>%
  group_by(`College Name`) %>%
  summarise(Total_Programs = n_distinct(`Instructional Program Class En Title`))

programs_merged <- merge(total_programs, ai_summary, by = "College Name", all.x = TRUE)
programs_merged[is.na(programs_merged)] <- 0

programs_merged <- programs_merged %>%
  rename(AI_Programs = P) %>%
  mutate(Percent_Label = paste0(
    round((AI_Programs / Total_Programs) * 100, 1), "% (",
    AI_Programs, "/", Total_Programs, ")"
  ))

programs_long <- programs_merged %>%
  pivot_longer(cols = c("AI_Programs", "Total_Programs"),
               names_to = "Program_Type", values_to = "Count")

# Sort by percentage of AI programs
programs_long$`College Name` <- factor(
  programs_long$`College Name`,
  levels = programs_merged$`College Name`[
    order(programs_merged$AI_Programs / programs_merged$Total_Programs, decreasing = TRUE)
  ]
)

programs_long$Program_Type <- factor(
```

```
  programs_long$Program_Type,
  levels = c("Total_Programs","AI_Programs")  # matches legend order and color map
)

# Plot 1
ggplot(programs_long, aes(x = `College Name`, y = Count, fill = Program_Type)) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.8)) +
  geom_text(data = subset(programs_long, Program_Type == "AI_Programs"),
          aes(label = programs_merged$Percent_Label),
          position = position_dodge(width = 0.8),
          hjust = -0.1, size = 2.5, color = "black") +
  scale_fill_manual(
    values = c("AI_Programs" = "steelblue", "Total_Programs" = "lightblue"),
    labels = c("ALL PROGRAMS","AI PROGRAMS"),
    name = "Program Type\n% (AI / ALL)"
  ) +
  coord_flip() +
  labs(title = "AI vs.Total Programs by College (2023–2024)",
      subtitle = "(Sorted by % of AI programs)",
      x = "College", y = "Number of Programs") +
  theme(
    legend.title = element_text(hjust = 0),
    legend.spacing.y = unit(0.4, 'lines'),
    legend.text = element_text(size = 8),
    plot.margin = margin(1, 1, 1, 1, "cm")
  )

# --- Page Break for PDF ---
cat('\\newpage\n')

# --- Plot 2: AI vs Total Students ---

summary_grid <- summary_grid %>%
  mutate(
    Student_Label = paste0(
      round((L_Raw / Total_Enrollment) * 100, 1), "% (",
      L_Raw, "/", Total_Enrollment, ")"
    )
  )

learners_long <- summary_grid %>%
  select(`College Name`, L_Raw, Total_Enrollment, Student_Label) %>%
  pivot_longer(cols = c("L_Raw", "Total_Enrollment"),
             names_to = "Enrollment_Type", values_to = "Count") %>%
  mutate(Enrollment_Type = recode(Enrollment_Type,
                          "L_Raw" = "AI Students",
                          "Total_Enrollment" = "All Students"))

# Sort by percentage of AI students
learners_long$`College Name` <- factor(
  learners_long$`College Name`,
  levels = summary_grid$`College Name`[
```

```
    order(summary_grid$L_Raw / summary_grid$Total_Enrollment, decreasing = TRUE)
  ]
)
learners_long$Enrollment_Type <- factor(
  learners_long$Enrollment_Type,
  levels = c("All Students","AI Students")
)


#Plot 2
ggplot(learners_long, aes(x = `College Name`, y = Count, fill = Enrollment_Type)) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.8)) +
  geom_text(data = subset(learners_long, Enrollment_Type == "AI Students"),
            aes(label = Student_Label),
            position = position_dodge(width = 0.8),
            hjust = -0.1, size = 2.5, color = "black") +
  scale_fill_manual(
    values = c("All Students" = "lightgreen","AI Students" = "darkgreen" ),
    labels = c("ALL STUDENTS","AI STUDENTS"),
    name = "Enrollment Type\n% (AI / ALL)"
  ) +
  coord_flip() +
  labs(title = "AI vs.Total Enrollment by College (2023–2024)",
       subtitle = "(Sorted by % of AI learners)",
       x = "College", y = "Number of Students") +
  theme(
    legend.title = element_text(hjust = 0),
    legend.spacing.y = unit(0.4, 'lines'),
    legend.text = element_text(size = 8),
    plot.margin = margin(1, 1, 1, 1, "cm")
  )
```

Appendix P:
GPLANET_P_L_Capstone.Rmd (R Markdown file)

G-PLANET-X P&L Summary
Carmel Tse
2025-05-11
Project Objectives
This Capstone Project marks the final requirement (Course 9 of 9) in the HarvardX Data Science Professional
Certificate program, delivered and supervised by Dr. Rafael Irizarry of the Harvard T.H. Chan School of Public Health.
The purpose of this project is to build a reproducible data pipeline in R that analyzes program offerings
and enrollment data across Ontario's community colleges, with a focus on disciplines related to Artificial
Intelligence (AI).
This project serves as a foundational input into the submitter's Global Doctor of Business Administration
(GDBA) dissertation at the Swiss School of Business and Management (SSBM), which investigates
AI Readiness in Ontario's Community Colleges in the context of the Fourth Industrial Revolution.
Specifically, the outputs from this R project feed into the P (Programs) and L (Learners) attributes of the G-PLANET-X framework, a composite scoring model used to quantify and compare AI integration across post-secondary institutions.
This project draws on open data available to the public by the Ministry of Colleges and Universities of the Government of Ontario.
Disclaimer 1:
The Ontario Open Data site does not allow for the automatic download of the dataset.
The data is published only in Excel spreadsheet format and requires manual download prior
to running this R script. URL: [Ontario College Enrolment Data (2023–2024) (https://data.ontario.ca/dataset/e9634682-b9dc-46a6-99b4-e17c86e00190)]
Disclaimer 2:
Collège Boréal did not report enrollment data for AI-related courses in the 2023–2024 dataset.
The college has submitted enrollment figures for other disciplines this year and had reported AI programs in previous years.
The omission is presumed to be a reporting gap, not an absence of programming.

```
# GPLANET_P_L_Capstone.R
# Purpose: Evaluate AI Readiness using P (Programs) and L (Learners) metrics
# across Ontario Colleges (2023–2024)
# --- Auto-Install and Load Required Packages ---
install_and_load <- function(pkg) {
if (!requireNamespace(pkg, quietly = TRUE)) {
install.packages(pkg, dependencies = TRUE)
}
1
library(pkg, character.only = TRUE)
}
install_and_load("readxl")
install_and_load("dplyr")
##
```

```
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
## filter, lag
## The following objects are masked from 'package:base':
##
## intersect, setdiff, setequal, union
install_and_load("ggplot2")
install_and_load("tidyr")
options(dplyr.print_max = Inf)
# --- Set Working Directory ---
setwd("C:/Projects/HarvardX Capstone/HarvardX")
file_path <- "college_enrolment_headcount_2023-24.xlsx"
# --- Load 2023–2024 CIP Data ---
cip_data <- read_excel(file_path, sheet = "CIP") %>%
filter(`Fiscal Year` == "2023-2024")
cip_data$`Headcount Full-Time Fall` <- as.numeric(cip_data$`Headcount Full-Time Fall`)
## Warning: NAs introduced by coercion
# --- AI-Relevant CIP Codes ---
ai_cips <- c(
"10.0304", "11.0101", "11.0102", "11.0103", "11.0104", "11.0199",
"11.0201", "11.0202", "11.0301", "11.0501", "11.0701", "11.0801",
"11.0802", "11.0804", "11.0899", "11.0901", "11.1001", "11.1002",
"11.1003", "11.1006", "11.1099", "11.9999", "15.0305", "15.0405",
"15.0406", "15.1201", "15.1202", "15.1204", "15.1299", "30.1601",
"45.0102", "47.0104", "47.0614", "48.0510", "51.2706", "52.0302",
"52.1201", "52.1206", "52.1299"
)#
--- Page Break for PDF ---
cat('\\newpage\n')
## \newpage
2
Table 1: Appendix A: AI-Relevant CIP Codes and Their Titles
CIP.Code Title
10.0304 Animation, interactive technology, video graphics and special effects
11.0101 Computer and information sciences, general
11.0102 Artificial intelligence
11.0103 Information technology
11.0104 Informatics
11.0199 Computer and information sciences and support services, general, other
11.0201 Computer programming/programmer, general
11.0202 Computer programming, specific applications
11.0301 Data processing and data processing technology/technician
11.0501 Computer systems analysis/analyst
11.0701 Computer science
11.0801 Web page, digital/multimedia and information resources design
11.0802 Data modelling/warehousing and database administration
11.0804 Modelling, virtual environments and simulation
11.0899 Computer software and media applications, other
11.0901 Computer systems networking and telecommunications, general
11.1001 Network and system administration/administrator
11.1002 System, networking and LAN/WAN management/manager
```

11.1003 Computer and information systems security/auditing/information assurance
11.1006 Computer support specialist
11.1099 Computer/information technology administration and management, other
11.9999 Computer and information sciences and support services, other
15.0305 Telecommunications technology/technician
15.0405 Robotics technology/technician
15.0406 Automation engineer technology/technician
15.1201 Computer engineering technology/technician, general
15.1202 Computer/computer systems technology/technician
15.1204 Computer software technology/technician
15.1299 Computer engineering technologies/technicians, other
30.1601 Accounting and computer science
45.0102 Research methodology and quantitative methods
47.0104 Computer installation and repair technology/technician
47.0614 Alternative fuel vehicle technology/technician
48.0510 CNC machinist technology/CNC machinist
51.2706 Medical informatics
52.0302 Accounting technology/technician and bookkeeping
52.1201 Management information systems, general
52.1206 Information resources management
52.1299 Management information systems and services, other
3
8.1% (12/148)
10.8% (8/74)
7% (4/57)
10.4% (13/125)
4.4% (2/45)
12.1% (17/140)
3.9% (2/51)
11.2% (11/98)
6.2% (7/113)
8.7% (8/92)
7.8% (9/116)
5.5% (7/127)
9% (6/67)
13.5% (12/89)
6.6% (4/61)
11% (10/91)
5% (4/80)
7.7% (3/39)
6.8% (4/59)
10.6% (14/132)
13.2% (12/91)
4.4% (4/91)
10% (9/90)
4.8% (3/62)
Lambton College
Sheridan College
Conestoga College
Durham College
Mohawk College
Cambrian College

Seneca College
Centennial College
St. Clair College
La Cité Collégiale
George Brown College
Algonquin College
Georgian College
Northern College
Canadore College
Sault College
Loyalist College
Fanshawe College
Humber College
Niagara College
St. Lawrence College
Collège Boréal
Sir Sandford Fleming College
Confederation College
0 50 100 150
Number of Programs
College
Program Type
% (AI / ALL)
ALL PROGRAMS
AI PROGRAMS
(Sorted by % of AI programs)
AI vs.Total Programs by College (2023–2024)
\newpage
4
16.1% (3395/21101)
5.6% (632/11278)
6.9% (641/9299)
13.4% (3245/24222)
0% (0/1705)
8.1% (3367/41374)
4.8% (175/3626)
13.5% (1694/12528)
3.7% (844/22680)
8.6% (1862/21707)
21% (3388/16154)
5.6% (1444/25846)
15.8% (972/6140)
11.2% (1589/14153)
16.3% (757/4641)
17.9% (2869/16049)
9.8% (1885/19151)
1.9% (129/6876)
5.6% (277/4920)
17.3% (4987/28801)
18.7% (4409/23567)
5% (557/11167)
15.7% (2499/15888)

0.9% (107/11563)
Georgian College
Sheridan College
Mohawk College
Seneca College
Loyalist College
Algonquin College
La Cité Collégiale
St. Clair College
Durham College
Centennial College
Lambton College
Niagara College
George Brown College
Conestoga College
Canadore College
Sault College
Cambrian College
Humber College
Sir Sandford Fleming College
Confederation College
Fanshawe College
Northern College
St. Lawrence College
Collège Boréal
0 10000 20000 30000 40000
Number of Students
College
Enrollment Type
% (AI / ALL)
ALL STUDENTS
AI STUDENTS
(Sorted by % of AI learners)
AI vs.Total Enrollment by College (2023–2024)
5

Appendix Q:
GPLANET_P_L_Capstone.pdf (summary output and plots)

G-PLANET-X P&L Summary
Carmel Tse
2025-05-11
Project Objectives
This Capstone Project marks the final requirement (Course 9 of 9) in the **HarvardX Data Science Professional Certificate** program, delivered and supervised by Dr. Rafael Irizarry of the Harvard T.H. Chan School of Public Health.
The purpose of this project is to build a reproducible data pipeline in R that analyzes program offerings and enrollment data across Ontario's community colleges, with a focus on disciplines related to Artificial Intelligence (AI).
This project serves as a **foundational input** into the submitter's Global Doctor of Business Administration (GDBA) dissertation at the **Swiss School of Business and Management (SSBM)**, which investigates **AI Readiness in Ontario's Community Colleges** in the context of the Fourth Industrial Revolution.
Specifically, the outputs from this R project feed into the **P (Programs)** and **L (Learners)** attributes of the **G-PLANET-X** framework, a composite scoring model used to quantify and compare AI integration across post-secondary institutions.
This project draws on open data available to the public by the **Ministry of Colleges and Universities** of the Government of Ontario.
Disclaimer 1:
The Ontario Open Data site does not allow for the automatic download of the dataset.
The data is published only in Excel spreadsheet format and requires **manual download** prior to running this R script. URL: [Ontario College Enrolment Data (2023–2024) (https://data. ontario.ca/dataset/e9634682-b9dc-46a6-99b4-e17c86e00190)]
Disclaimer 2:
Collège Boréal did not report enrollment data for AI-related courses in the 2023–2024 dataset. The college has submitted enrollment figures for other disciplines this year and had reported AI programs in previous years.
The omission is presumed to be a reporting gap, not an absence of programming.

```
# GPLANET_P_L_Capstone.R
# Purpose: Evaluate AI Readiness using P (Programs) and L (Learners) metrics
# across Ontario Colleges (2023–2024)
# --- Auto-Install and Load Required Packages --install_and_load <- function(pkg) { if
(!requireNamespace(pkg, quietly = TRUE)) { install.packages(pkg, dependencies =
TRUE) }
```

```
library(pkg, character.only = TRUE)
}
install_and_load("readxl") install_and_load("dplyr")
```

```
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
........................................................................ filte
r, lag
## The following objects are masked from 'package:base':
##
##
........................................................................ inte
rsect, setdiff, setequal, union
```

```
install_and_load("ggplot2") install_and_load("tidyr") options(dplyr.print_max = Inf)
# --- Set Working Directory ---
setwd("C:/Projects/HarvardX Capstone/HarvardX") file_path <-
"college_enrolment_headcount_2023-24.xlsx"
# --- Load 2023–2024 CIP Data ---
cip_data <- read_excel(file_path, sheet = "CIP") %>% filter(`Fiscal Year` == "2023-2024")
cip_data$`Headcount Full-Time Fall` <- as.numeric(cip_data$`Headcount Full-Time Fall`)
```

```
## Warning: NAs introduced by coercion
```

```
# --- AI-Relevant CIP Codes --ai_cips <- c(
"10.0304", "11.0101", "11.0102", "11.0103", "11.0104", "11.0199", "11.0201", "11.0202",
"11.0301", "11.0501", "11.0701", "11.0801", "11.0802", "11.0804", "11.0899", "11.0901",
"11.1001", "11.1002", "11.1003", "11.1006", "11.1099", "11.9999", "15.0305", "15.0405",
"15.0406", "15.1201", "15.1202", "15.1204", "15.1299", "30.1601",
"45.0102", "47.0104", "47.0614", "48.0510", "51.2706", "52.0302", "52.1201", "52.1206",
"52.1299"
)
# --- Page Break for PDF ---
cat('\\newpage\n')
```

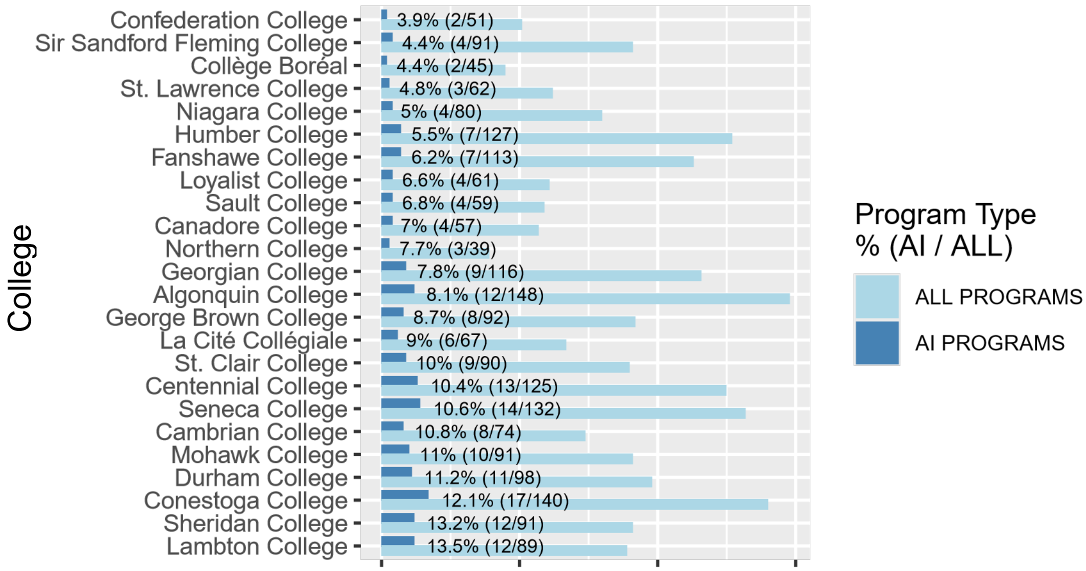
```
## \newpage
```

Table 1: Appendix A: AI-Relevant CIP Codes and Their Titles

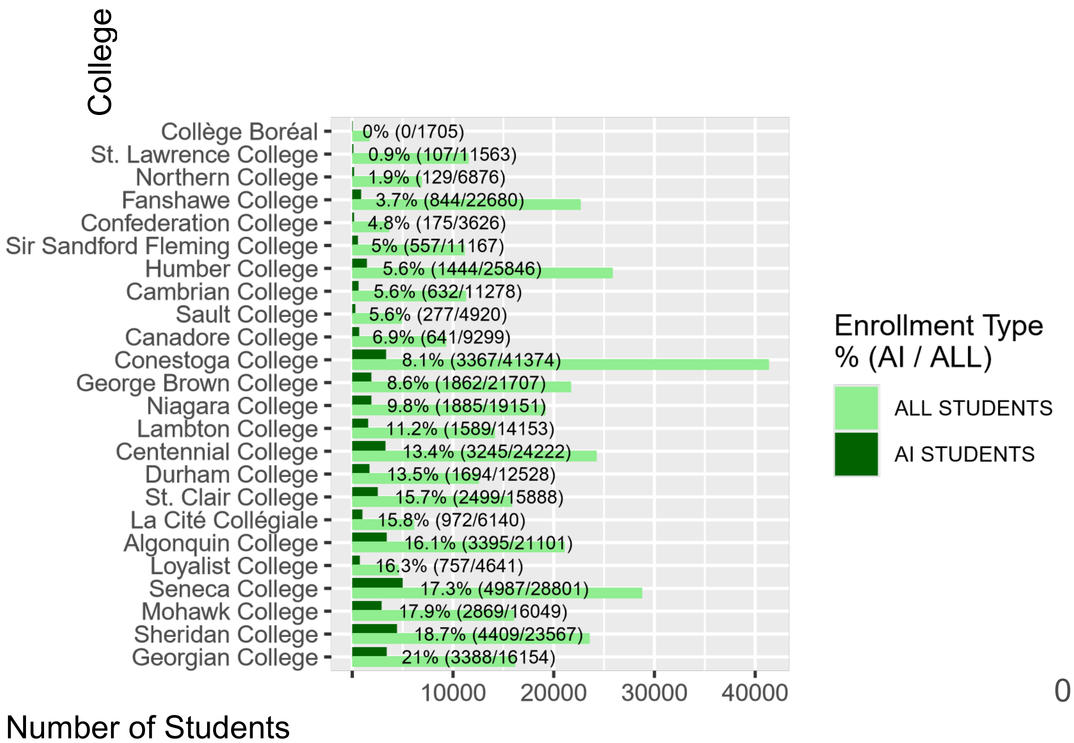
CIP.Code	Title
10.0304	Animation, interactive technology, video graphics and special effects

11.0101	Computer and information sciences, general
11.0102	Artificial intelligence
11.0103	Information technology
11.0104	Informatics
11.0199	Computer and information sciences and support services, general, other
11.0201	Computer programming/programmer, general
11.0202	Computer programming, specific applications
11.0301	Data processing and data processing technology/technician
11.0501	Computer systems analysis/analyst
11.0701	Computer science
11.0801	Web page, digital/multimedia and information resources design
11.0802	Data modelling/warehousing and database administration
11.0804	Modelling, virtual environments and simulation
11.0899	Computer software and media applications, other
11.0901	Computer systems networking and telecommunications, general
11.1001	Network and system administration/administrator
11.1002	System, networking and LAN/WAN management/manager
11.1003	Computer and information systems security/auditing/information assurance
11.1006	Computer support specialist
11.1099	Computer/information technology administration and management, other
11.9999	Computer and information sciences and support services, other
15.0305	Telecommunications technology/technician
15.0405	Robotics technology/technician
15.0406	Automation engineer technology/technician
15.1201	Computer engineering technology/technician, general
15.1202	Computer/computer systems technology/technician
15.1204	Computer software technology/technician
15.1299	Computer engineering technologies/technicians, other
30.1601	Accounting and computer science
45.0102	Research methodology and quantitative methods
47.0104	Computer installation and repair technology/technician
47.0614	Alternative fuel vehicle technology/technician
48.0510	CNC machinist technology/CNC machinist
51.2706	Medical informatics
52.0302	Accounting technology/technician and bookkeeping
52.1201	Management information systems, general
52.1206	Information resources management
52.1299	Management information systems and services, other

AI vs.Total Programs by College (2023–2024)
(Sorted by % of AI programs)



0
50
100
150
Number of Programs
\newpage
AI vs.Total Enrollment by College (2023–2024)
(Sorted by % of AI learners)


College
Collège Boréal
St. Lawrence College
Northern College
Fanshawe College
Confederation College
Sir Sandford Fleming College
Humber College
Cambrian College
Sault College
Canadore College
Conestoga College
George Brown College
Niagara College
Lambton College
Centennial College
Durham College
St. Clair College
La Cité Collégiale
Algonquin College
Loyalist College
Seneca College
Mohawk College
Sheridan College
Georgian College
0% (0/1705)
0.9% (107/11563)
1.9% (129/6876)
3.7% (844/22680)
4.8% (175/3626)
5% (557/11167)
5.6% (1444/25846)
5.6% (632/11278)
5.6% (277/4920)
6.9% (641/9299)
8.1% (3367/41374)
8.6% (1862/21707)
9.8% (1885/19151)
11.2% (1589/14153)
13.4% (3245/24222)
13.5% (1694/12528)
15.7% (2499/15888)
15.8% (972/6140)
16.1% (3395/21101)
16.3% (757/4641)
17.3% (4987/28801)
17.9% (2869/16049)
18.7% (4409/23567)
21% (3388/16154)
10000
20000
30000
40000
0
Number of Students
Enrollment Type
% (AI / ALL)
ALL STUDENTS
AI STUDENTS

Appendix R:
SMA_Scorer_LLM_v4.py (Python Chatbot script)

```
from openai import OpenAI
from docx import Document
import pandas as pd
import re
import os
import time

# ========== CONFIG ==========
MODEL_NAME = "gpt-4-1106-preview"
INPUT_DOCX = "SMA Extracted Text.docx"
OUTPUT_DIR = "SMA_Evals"
CSV_OUTPUT = "SMA_Eval_Scores.csv"
os.makedirs(OUTPUT_DIR, exist_ok=True)

# ========== LOAD RUBRIC ==========
rubric_path = "SMA_AI_Scoring_Rubric_Grid.xlsx"
rubric_df = pd.read_excel(rubric_path)

# Format rubric text for injection
rubric_prompt_blocks = []
for dimension, group in rubric_df.groupby("Dimension"):
    block = f"### {dimension}\n"
    for _, row in group.sort_values("Score").iterrows():
        block += f"- **Score {int(row['Score'])}**: {row['Scoring Description']}\n"
    rubric_prompt_blocks.append(block)

rubric_prompt_text = (
    "Please evaluate the following Strategic Mandate Agreement (SMA) using the rubric below. "
    "Assign a score (0–10) for each dimension based on the provided scale. "
    "Format each response like this:\n\n"
    "Dimension: [Name]\nScore: [Number]\nJustification: [1–2 sentences]\n\n"
    "RUBRIC:\n\n" + "\n\n".join(rubric_prompt_blocks)
)

# ========== LOAD SMA TEXT ==========
doc = Document(INPUT_DOCX)
full_text = "\n".join([para.text for para in doc.paragraphs])
chapter_splits = re.split(r"(Chapter \d+: [^\n]+)", full_text)
chapter_splits = [part.strip() for part in chapter_splits if part.strip()]
chapters = {
    chapter_splits[i]: chapter_splits[i + 1]
    for i in range(0, len(chapter_splits) - 1, 2)
}

# ========== PROCESS EACH CHAPTER ==========
client = OpenAI()
all_scores = []

for title, content in chapters.items():
```

```
    college_name = title.replace("Chapter", "").strip()
    print(f"\n🔍 Scoring {college_name}...")

    try:
        # Compose full prompt
        prompt = rubric_prompt_text + f"\n\nSMA TEXT:\n\n{content}"

        response = client.chat.completions.create(
            model=MODEL_NAME,
            messages=[
                {"role": "system", "content": "You are an expert evaluator of AI in education policy."},
                {"role": "user", "content": prompt}
            ],
            temperature=0.0
        )

        response_text = response.choices[0].message.content.strip()

        # Save raw response
        safe_name = re.sub(r'[^\w\-]', '_', college_name)
        timestamp = time.strftime("%Y%m%d-%H%M%S")
        txt_path = os.path.join(OUTPUT_DIR, f"LLM_Eval_{safe_name}_{timestamp}.txt")
        with open(txt_path, "w", encoding="utf-8") as f:
            f.write(response_text)

        # Extract dimension scores using regex
        score_lines = re.findall(r"Dimension:\s*(.*?)\nScore:\s*(\d+)", response_text)
        for dim, score in score_lines:
            all_scores.append({
                "College": college_name,
                "Dimension": dim.strip(),
                "Score": int(score)
            })

        print(f"✅ Scored {college_name}. Saved to {txt_path}")

    except Exception as e:
        print(f"❌ Error scoring {college_name}: {e}")

# ========== SAVE CONSOLIDATED CSV ==========
if all_scores:
    scores_df = pd.DataFrame(all_scores)
    scores_df.to_csv(CSV_OUTPUT, index=False)
    print(f"\n📄 All scores saved to {CSV_OUTPUT}")
else:
    print("\n⚠️ No scores to save.")
```

Appendix S:
SAM URLs.xlsx (Source SMAs)

Institution	SMA URL
Algonquin	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-algonquin-colle
Boreal	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-college-boreal-
Cambrian	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-cambrian-colle
Canadore	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-canadore-colle
Centennial	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-centennial-coll
Conestoga	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-conestoga-colle
Confederation	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-confederation-
Durham	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-durham-college
Fanshawe	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-fanshawe-colle
Fleming	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-sir-sandford-fle
George Brown	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-george-brown-
Georgian	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-georgian-colleg
Humber	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-humber-college
La Cite	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-college-darts-a
Lambton	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-lambton-colleg
Loyalist	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-loyalist-college-
Mohawk	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-mohawk-colleg
Niagara	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-niagara-college
Northern	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-northern-colleg
Sault	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-sault-college-ap
Seneca	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-seneca-college-
Sheridan	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-sheridan-colleg
St. Clair	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-st-clair-college-
St. Lawrence	https://www.ontario.ca/page/2020-2025-strategic-mandate-agreement-st-lawrence-col

Appendix T:
SMA_College_Summaries.txt (Summary output)

Algonquin
Algonquin demonstrates moderate alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 2.8 across the five dimensions. The institution shows performance levels of AI-Related Programming (2), Applied Research in AI (2), Community / Industry Partnerships (4), Strategic AI Commitment (2), Workforce Alignment (4). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Applied Research in AI, Strategic AI Commitment represent opportunities for deeper alignment. Overall, Algonquin occupies a middle-tier position in aligning its SMA with AI integration, offering a stable foundation for enhancement in future agreements.

Boreal
Boreal demonstrates moderate alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 2.4 across the five dimensions. The institution shows performance levels of AI-Related Programming (2), Applied Research in AI (0), Community / Industry Partnerships (4), Strategic AI Commitment (2), Workforce Alignment (4). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as Applied Research in AI represent opportunities for deeper alignment. Overall, Boreal occupies a middle-tier position in aligning its SMA with AI integration, offering a stable foundation for enhancement in future agreements.

Cambrian
Cambrian demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 4.0 across the five dimensions. The institution shows performance levels of AI-Related Programming (2), Applied Research in AI (4), Community / Industry Partnerships (4), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in Workforce Alignment, while areas such as AI-Related Programming represent opportunities for deeper alignment. Overall, Cambrian is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Canadore
Canadore demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 4.0 across the five dimensions. The institution shows performance levels of AI-Related Programming (4), Applied Research in AI (4), Community / Industry Partnerships (4), Strategic AI Commitment (4), Workforce Alignment (4). This uniform scoring suggests a balanced institutional stance on AI, without clear strengths or weaknesses in any specific area. Overall, Canadore is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Centennial
Centennial demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 5.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (6), Applied Research in AI (6), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in AI-Related Programming, Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as Strategic AI Commitment represent opportunities for deeper alignment. Overall, Centennial is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Conestoga
Conestoga demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 4.0 across the five dimensions. The institution shows performance levels of AI-Related Programming (2), Applied Research in AI (4), Community / Industry Partnerships (4), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in Workforce Alignment, while areas such as AI-Related Programming represent opportunities for deeper alignment. Overall, Conestoga is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Confederation
Confederation demonstrates minimal alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 1.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (0), Applied Research in AI (0), Community / Industry Partnerships (4), Strategic AI Commitment (0), Workforce Alignment (4). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Applied Research in AI, Strategic AI Commitment represent opportunities for deeper alignment. Overall, Confederation falls behind most institutions in aligning its SMA with AI integration, offering significant room for improvement in future agreements.

Durham
Durham demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 5.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (6), Applied Research in AI (6), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in AI-Related Programming, Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as Strategic AI Commitment represent opportunities for deeper alignment. Overall, Durham is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Fanshawe
Fanshawe demonstrates minimal alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 1.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (0), Applied Research in AI (0), Community / Industry Partnerships (4), Strategic AI Commitment (0), Workforce Alignment (4). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Applied Research in AI, Strategic AI Commitment represent opportunities for deeper alignment. Overall, Fanshawe falls behind most institutions in aligning its SMA with AI integration, offering significant room for improvement in future agreements.

Fleming
Fleming demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 4.8 across the five dimensions. The institution shows performance levels of AI-Related Programming (4), Applied Research in AI (4), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Applied Research in AI, Strategic AI Commitment represent opportunities for deeper alignment. Overall, Fleming is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

George Brown

George Brown demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 5.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (6), Applied Research in AI (6), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in AI-Related Programming, Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as Strategic AI Commitment represent opportunities for deeper alignment. Overall, George Brown is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Georgian

Georgian demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 5.2 across the five dimensions. The institution shows performance levels of AI-Related Programming (4), Applied Research in AI (6), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Strategic AI Commitment represent opportunities for deeper alignment. Overall, Georgian is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Humber

Humber demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 5.2 across the five dimensions. The institution shows performance levels of AI-Related Programming (4), Applied Research in AI (6), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Strategic AI Commitment represent opportunities for deeper alignment. Overall, Humber is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

La Cite

La Cite demonstrates moderate alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 3.2 across the five dimensions. The institution shows performance levels of AI-Related Programming (2), Applied Research in AI (4), Community / Industry Partnerships (4), Strategic AI Commitment (2), Workforce Alignment (4). Particular strengths are noted in Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Strategic AI Commitment represent opportunities for deeper alignment. Overall, La Cite occupies a middle-tier position in aligning its SMA with AI integration, offering a stable foundation for enhancement in future agreements.

Lambton

Lambton demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 6.0 across the five dimensions. The institution shows performance levels of AI-Related Programming (6), Applied Research in AI (8), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in Applied Research in AI, while areas such as Strategic AI Commitment represent opportunities for deeper alignment. Overall, Lambton is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Loyalist
Loyalist demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 5.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (6), Applied Research in AI (6), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in AI-Related Programming, Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as Strategic AI Commitment represent opportunities for deeper alignment. Overall, Loyalist is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Mohawk
Mohawk demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 4.8 across the five dimensions. The institution shows performance levels of AI-Related Programming (4), Applied Research in AI (4), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Applied Research in AI, Strategic AI Commitment represent opportunities for deeper alignment. Overall, Mohawk is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Niagara
Niagara demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 4.0 across the five dimensions. The institution shows performance levels of AI-Related Programming (2), Applied Research in AI (6), Community / Industry Partnerships (4), Strategic AI Commitment (4), Workforce Alignment (4). Particular strengths are noted in Applied Research in AI, while areas such as AI-Related Programming represent opportunities for deeper alignment. Overall, Niagara is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Northern
Northern demonstrates moderate alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 3.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (2), Applied Research in AI (4), Community / Industry Partnerships (6), Strategic AI Commitment (2), Workforce Alignment (4). Particular strengths are noted in Community / Industry Partnerships, while areas such as AI-Related Programming, Strategic AI Commitment represent opportunities for deeper alignment. Overall, Northern occupies a middle-tier position in aligning its SMA with AI integration, offering a stable foundation for enhancement in future agreements.

Sault
Sault demonstrates moderate alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 2.4 across the five dimensions. The institution shows performance levels of AI-Related Programming (2), Applied Research in AI (0), Community / Industry Partnerships (4), Strategic AI Commitment (2), Workforce Alignment (4). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as Applied

Research in AI represent opportunities for deeper alignment. Overall, Sault occupies a middle-tier position in aligning its SMA with AI integration, offering a stable foundation for enhancement in future agreements.

Seneca

Seneca demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 5.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (6), Applied Research in AI (6), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in AI-Related Programming, Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as Strategic AI Commitment represent opportunities for deeper alignment. Overall, Seneca is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

Sheridan

Sheridan demonstrates strong alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 5.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (6), Applied Research in AI (6), Community / Industry Partnerships (6), Strategic AI Commitment (4), Workforce Alignment (6). Particular strengths are noted in AI-Related Programming, Applied Research in AI, Community / Industry Partnerships, Workforce Alignment, while areas such as Strategic AI Commitment represent opportunities for deeper alignment. Overall, Sheridan is among the provincial leaders in aligning its SMA with AI integration, offering a strong platform for sustained AI integration in future agreements.

St. Clair

St. Clair demonstrates minimal alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 1.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (0), Applied Research in AI (0), Community / Industry Partnerships (4), Strategic AI Commitment (0), Workforce Alignment (4). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Applied Research in AI, Strategic AI Commitment represent opportunities for deeper alignment. Overall, St. Clair falls behind most institutions in aligning its SMA with AI integration, offering significant room for improvement in future agreements.

St. Lawrence

St. Lawrence demonstrates minimal alignment with AI-related objectives in its Strategic Mandate Agreement (SMA), earning an average rubric score of 1.6 across the five dimensions. The institution shows performance levels of AI-Related Programming (0), Applied Research in AI (0), Community / Industry Partnerships (4), Strategic AI Commitment (0), Workforce Alignment (4). Particular strengths are noted in Community / Industry Partnerships, Workforce Alignment, while areas such as AI-Related Programming, Applied Research in AI, Strategic AI Commitment represent opportunities for deeper alignment. Overall, St. Lawrence falls behind most institutions in aligning its SMA with AI integration, offering significant room for improvement in future agreements.

Appendix U:
CIP_parser.R (R script)

```
setwd("C:/Projects/HarvardX Capstone/CIP")
file_path <- "college_enrolment_CIP_2023-24.xlsx"
cip_data <- readxl::read_excel(file_path)

# CIP_parser.R
# Purpose: Analyze AI Readiness by counting unique AI-relevant CIP codes per college
# Dataset: college_enrolment_CIP_2023-24.xlsx
# Location: Same directory as this script

# --- Auto-Install and Load Required Packages ---
install_and_load <- function(pkg) {
  if (!requireNamespace(pkg, quietly = TRUE)) {
    install.packages(pkg, dependencies = TRUE)
  }
  library(pkg, character.only = TRUE)
}

install_and_load("readxl")
install_and_load("dplyr")
install_and_load("ggplot2")

# --- Set Working Directory to Current Script Folder ---
setwd("C:/Projects/HarvardX Capstone/CIP")

# --- Load Data ---
file_path <- "college_enrolment_CIP_2023-24.xlsx"
cip_data <- read_excel(file_path)

# --- Filter for 2023–2024 Academic Year ---
cip_data <- cip_data %>%
  filter(`Fiscal Year` == "2023-2024")

# --- Define AI-Relevant CIP Codes (CIP-39) ---
ai_cips <- c(
  "10.0304", "11.0101", "11.0102", "11.0103", "11.0104", "11.0199",
  "11.0201", "11.0202", "11.0301", "11.0501", "11.0701", "11.0801",
  "11.0802", "11.0804", "11.0899", "11.0901", "11.1001", "11.1002",
  "11.1003", "11.1006", "11.1099", "11.9999", "15.0305", "15.0405",
  "15.0406", "15.1201", "15.1202", "15.1204", "15.1299", "30.1601",
  "45.0102", "47.0104", "47.0614", "48.0510", "51.2706", "52.0302",
  "52.1201", "52.1206", "52.1299"
)

# --- Filter AI Programs Only ---
ai_programs <- cip_data %>%
  filter(`Instructional Program Class Code` %in% ai_cips)
```

```
# --- Count Unique CIP Codes by College ---
cip_variety <- ai_programs %>%
  group_by(`College Name`) %>%
  summarise(Unique_AI_CIP_Count = n_distinct(`Instructional Program Class Code`)) %>%
  arrange(desc(Unique_AI_CIP_Count))

# --- Print Results ---
print(cip_variety)

# --- Plot Chart: CIP Variety by College ---
ggplot(cip_variety, aes(x = reorder(`College Name`, Unique_AI_CIP_Count), y =
Unique_AI_CIP_Count)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
  labs(
    title = "AI-Relevant CIP Code Variety by College (2023–2024)",
    x = "College",
    y = "Unique AI CIP Codes Offered"
  ) +
  theme_minimal()

# --- Optional: Export to CSV ---
write.csv(cip_variety, "AI_CIP_Variety_by_College.csv", row.names = FALSE)
```

Appendix V:
AI CIP Variety Analysis-1.Rmd (R Markdown file)

```
AI CIP Variety Analysis
Carmel Tse
# Load Excel data
cip_data <- read_excel("college_enrolment_CIP_2023-24.xlsx")

# Filter for academic year
cip_data <- cip_data %>% filter(`Fiscal Year` == "2023-2024")

# Define 39 AI-relevant CIP codes
ai_cips <- c("10.0304", "11.0101", "11.0102", "11.0103", "11.0104", "11.0199",
        "11.0201", "11.0202", "11.0301", "11.0501", "11.0701", "11.0801",
        "11.0802", "11.0804", "11.0899", "11.0901", "11.1001", "11.1002",
        "11.1003", "11.1006", "11.1099", "11.9999", "15.0305", "15.0405",
        "15.0406", "15.1201", "15.1202", "15.1204", "15.1299", "30.1601",
        "45.0102", "47.0104", "47.0614", "48.0510", "51.2706", "52.0302",
        "52.1201", "52.1206", "52.1299")

# Filter AI programs
ai_programs <- cip_data %>% filter(`Instructional Program Class Code` %in% ai_cips)

# Calculate unique CIP counts per college
cip_variety <- ai_programs %>%
  group_by(`College Name`) %>%
  summarise(Unique_AI_CIP_Count = n_distinct(`Instructional Program Class Code`)) %>%
  arrange(desc(Unique_AI_CIP_Count))

# Show the results
cip_variety
## # A tibble: 24 × 2
##    `College Name`     Unique_AI_CIP_Count
##    <chr>                            <int>
##  1 Conestoga College                   17
##  2 Seneca College                      14
##  3 Centennial College                  13
##  4 Algonquin College                   12
##  5 Lambton College                     12
##  6 Sheridan College                    12
##  7 Durham College                      11
##  8 Mohawk College                      10
##  9 Georgian College                     9
## 10 St. Clair College                    9
## # ℹ 14 more rows
cip_variety <- cip_variety %>%
  mutate(Percent_Coverage = round(100 * Unique_AI_CIP_Count / 39, 1))
print(cip_variety, n = Inf)
## # A tibble: 24 × 3
##    `College Name`              Unique_AI_CIP_Count Percent_Coverage
##    <chr>                                     <int>            <dbl>
```

```
## 1 Conestoga College 17 43.6
## 2 Seneca College 14 35.9
## 3 Centennial College 13 33.3
## 4 Algonquin College 12 30.8
## 5 Lambton College 12 30.8
## 6 Sheridan College 12 30.8
## 7 Durham College 11 28.2
## 8 Mohawk College 10 25.6
## 9 Georgian College 9 23.1
## 10 St. Clair College 9 23.1
## 11 Cambrian College 8 20.5
## 12 George Brown College 8 20.5
## 13 Fanshawe College 7 17.9
## 14 Humber College 7 17.9
## 15 La Cité Collégiale 6 15.4
## 16 Canadore College 4 10.3
## 17 Loyalist College 4 10.3
## 18 Niagara College 4 10.3
## 19 Sault College 4 10.3
## 20 Sir Sandford Fleming College 4 10.3
## 21 Northern College 3 7.7
## 22 St. Lawrence College 3 7.7
## 23 Collège Boréal 2 5.1
## 24 Confederation College 2 5.1
ggplot(cip_variety, aes(x = reorder(`College Name`, Unique_AI_CIP_Count), y =
Unique_AI_CIP_Count)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  geom_text(aes(label = paste0(Percent_Coverage, "%")), hjust = -0.1, size = 3.5) +
  coord_flip() +
  labs(
    title = "AI-Relevant CIP Variety by College (2023–2024)",
    x = "College",
    y = "Unique AI CIP Codes (of 39)"
  ) +
  theme_minimal() +
  ylim(0, max(cip_variety$Unique_AI_CIP_Count) + 3)
)

# --- Display Result ---
print(cip_variety)

# --- Optional: Plot Variety by College ---
ggplot(cip_variety, aes(x = reorder(`College Name`, Unique_AI_CIP_Count), y =
Unique_AI_CIP_Count)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
  labs(
    title = "AI CIP Code Variety by College (2023–2024)",
    x = "College",
    y = "Unique AI-Relevant CIP Codes"
  ) +
  theme_minimal()
```

Appendix W:
AI CIP Variety Analysis-1.pdf (summary output and plots)

AI CIP Variety Analysis

Carmel Tse

```
# Load Excel data
cip_data <- read_excel("college_enrolment_CIP_2023-24.xlsx")

# Filter for academic year
cip_data <- cip_data %>% filter(`Fiscal Year` == "2023-2024")

# Define 39 AI-relevant CIP codes
ai_cips <- c("10.0304", "11.0101", "11.0102", "11.0103", "11.0104
", "11.0199",
             "11.0201", "11.0202", "11.0301", "11.0501", "11.0701
", "11.0801",
             "11.0802", "11.0804", "11.0899", "11.0901", "11.1001
", "11.1002",
             "11.1003", "11.1006", "11.1099", "11.9999", "15.0305
", "15.0405",
             "15.0406", "15.1201", "15.1202", "15.1204", "15.1299
", "30.1601",
             "45.0102", "47.0104", "47.0614", "48.0510", "51.2706
", "52.0302",
             "52.1201", "52.1206", "52.1299")

# Filter AI programs
ai_programs <- cip_data %>% filter(`Instructional Program Class C
ode` %in% ai_cips)

# Calculate unique CIP counts per college
cip_variety <- ai_programs %>%
  group_by(`College Name`) %>%
  summarise(Unique_AI_CIP_Count = n_distinct(`Instructional Progr
am Class Code`)) %>%
  arrange(desc(Unique_AI_CIP_Count))

# Show the results
cip_variety

## # A tibble: 24 × 2
##    `College Name`     Unique_AI_CIP_Count
##    <chr>                            <int>
##  1 Conestoga College                   17
```

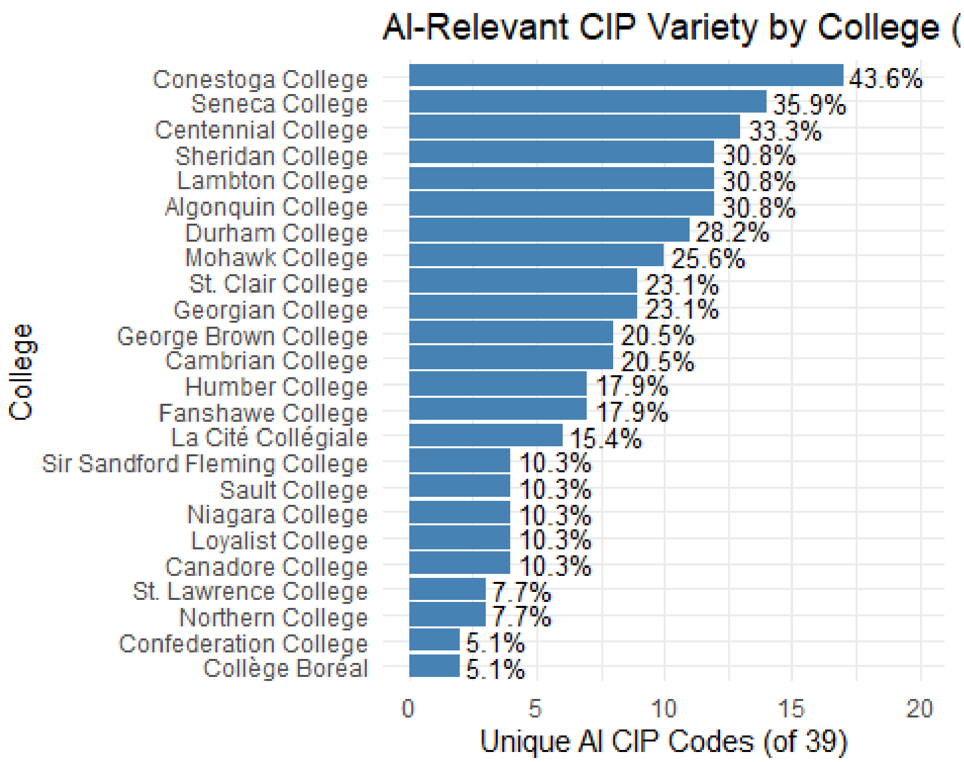
```
##   2 Seneca College                       14
##   3 Centennial College                   13
##   4 Algonquin College                    12
##   5 Lambton College                      12
##   6 Sheridan College                     12
##   7 Durham College                       11
##   8 Mohawk College                       10
##   9 Georgian College                      9
##  10 St. Clair College                     9
## # ℹ 14 more rows
```

```
cip_variety <- cip_variety %>%
  mutate(Percent_Coverage = round(100 * Unique_AI_CIP_Count / 39,
 1))
print(cip_variety, n = Inf)
```

```
## # A tibble: 24 × 3
##    `College Name`                   Unique_AI_CIP_Count Percent_Co
verage
##    <chr>                                          <int>
 <dbl>
##   1 Conestoga College                                17
  43.6
##   2 Seneca College                                   14
  35.9
##   3 Centennial College                               13
  33.3
##   4 Algonquin College                                12
  30.8
##   5 Lambton College                                  12
  30.8
##   6 Sheridan College                                 12
  30.8
##   7 Durham College                                   11
  28.2
##   8 Mohawk College                                   10
  25.6
##   9 Georgian College                                  9
  23.1
##  10 St. Clair College                                 9
  23.1
##  11 Cambrian College                                  8
  20.5
##  12 George Brown College                              8
  20.5
##  13 Fanshawe College                                  7
```

```
  17.9
## 14 Humber College                                     7
  17.9
## 15 La Cité Collégiale                                 6
  15.4
## 16 Canadore College                                   4
  10.3
## 17 Loyalist College                                   4
  10.3
## 18 Niagara College                                    4
  10.3
## 19 Sault College                                      4
  10.3
## 20 Sir Sandford Fleming College                       4
  10.3
## 21 Northern College                                   3
   7.7
## 22 St. Lawrence College                               3
   7.7
## 23 Collège Boréal                                     2
   5.1
## 24 Confederation College                              2
   5.1
```

```
ggplot(cip_variety, aes(x = reorder(`College Name`, Unique_AI_CIP
_Count), y = Unique_AI_CIP_Count)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  geom_text(aes(label = paste0(Percent_Coverage, "%")), hjust = -
0.1, size = 3.5) +
  coord_flip() +
  labs(
    title = "AI-Relevant CIP Variety by College (2023–2024)",
    x = "College",
    y = "Unique AI CIP Codes (of 39)"
  ) +
  theme_minimal() +
  ylim(0, max(cip_variety$Unique_AI_CIP_Count) + 3)
```


AI-Relevant CIP Variety by College (
College
Conestoga College
Seneca College
Centennial College
Sheridan College
Lambton College
Algonquin College
Durham College
Mohawk College
St. Clair College
Georgian College
George Brown College
Cambrian College
Humber College
Fanshawe College
La Cité Collégiale
Sir Sandford Fleming College
Sault College
Niagara College
Loyalist College
Canadore College
St. Lawrence College
Northern College
Confederation College
Collège Boréal
43.6%
35.9%
33.3%
30.8%
30.8%
30.8%
28.2%
25.6%
23.1%
23.1%
20.5%
20.5%
17.9%
17.9%
15.4%
10.3%
10.3%
10.3%
10.3%
10.3%
7.7%
7.7%
5.1%
5.1%
0
5
10
15
20
Unique AI CIP Codes (of 39)