Comparing Artificial Intelligence Curricula in Canadian and US Universities

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Abstract

Artificial Intelligence (AI) has impacted the world tremendously in the last decade, causing an increased demand for accessible AI education globally. Students benefit from studying AI earlier in the curriculum; however, AI courses can require a range of prerequisites, which can be structured differently in various educational contexts. In this paper, we study the curriculum structure of AI, Machine Learning (ML), and Data Science (DS) courses in Canadian Universities and compare it with that of US Research-1 institutions. There are many similarities between AI, ML, and DS courses in Canada and the US. For example, DS courses tend to be more accessible earlier in the CS curriculum compared to AI and ML. However, there are key differences between the two countries, with Canadian AI, ML, and DS courses generally being a part of a longer prerequisites chain, and Canadian CS departments offering fewer DS courses. Still, both Canadian and US institutions find innovative ways to introduce AI earlier in the curriculum, including via interdisciplinary courses and specialized courses with few prerequisites. This study corroborates earlier work in recognizing diversity in curricular frameworks in North America and recommends curricular revisions and early academic advising to ensure access to AI courses.

Introduction

The rapid rise of Artificial Intelligence (AI) has influenced many different industry sectors (Espina-Romero et al. 2023). Acknowledging the influence of AI, the number of university programs focused on AI has more than doubled over the past five years (Maslej et al. 2024). In addition, the Computer Science Curricular Guidelines (CSC2023) now include 5 hours of Basic Machine Learning (Servin et al. 2024). Therefore, implementing relevant and attractive AI curricula early in students' academic careers is crucial in motivating the next generation (Renz and Hilbig 2020; Chiu et al. 2021; Touretzky et al. 2019). In particular, AI, Machine Learning (ML), and Data Science (DS) (referred to collectively as *AI* here on) courses play a key role in shaping the AI curricula.

Previously, we conducted a study analyzing the prerequisite structures of *AI* courses in US Research-1 (R1) institutions (Niousha et al. 2024), revealing variability in the accessibility of *AI* courses. We found that while DS courses typically required fewer prerequisites and allowed for earlier exposure, *AI* courses often demanded more advanced preparation in programming and mathematics.

This study explores how our framework for analyzing *AI* curricula translates outside of the US. We examine whether the trends and challenges observed are consistent across educational systems. As an immediate next step, we chose Canada because it shares several structural similarities with the US—such as a strong research focus and high-quality education—yet differs in its centralized education system and heavy reliance on public institutions. These similarities allow for a meaningful comparison, while the differences offer valuable insights into how curriculum structures in *AI* can be adapted to various contexts.

Thus, in this study, we replicated our previous analysis (Niousha et al. 2024) in the context of Canadian universities, exploring how *AI* courses are structured and how their prerequisites compare to those in the US. By contrasting the approaches used in Canada and the US, our goal is to identify best practices from each system that can enhance curriculum design. We aim to answer the following questions:

- **RQ1:** What approaches are institutions using to structure prerequisites for *AI* courses in Canada?
- **RQ2:** What are the similarities and differences in prerequisite structure of *AI* courses between US and Canada?
- **RQ3:** What approaches are effective to allow early exposure of *AI* for undergraduate students in the US and Canada?

This comparison also paves the way to enhance the generalizability of our methodology, so that it can be adapted to assess *AI* curricula in other countries, providing a broader framework for educational institutions globally.

Related Work

Importance of Teaching AI

Teaching *AI* at the university level is a well-established topic in CS education (Shapiro, Fiebrink, and Norvig 2018; Ng et al. 2023). While the popularity of *AI* courses is growing, research on best practices for teaching these subjects, which require a strong foundation in computing and mathematics, remains limited (Allen, McGough, and Devlin 2021).

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Apart from the complex theories and knowledge, students may prefer applied AI, focusing on practical problem-solving over complex theories (Zheng 2019). DS courses are particularly suited to providing these hands-on skills considering their overlap in AI concepts (Spector 2024). However, given that DS courses are still in their forming stages and are highly interdisciplinary, how to teach such courses or prepare for varying levels of preparation for students is only beginning to be explored (Mike, Hazan, and Hazzan 2020; Schwab-McCoy, Baker, and Gasper 2021).

There is substantial literature on teaching AI to non-CS students, offering potential inspiration for approaches to introduce AI earlier or improve academic advising (Danyluk 2008; Lee and Cho 2021; Meyer and Fausser 2022). Moreover, AI is so ubiquitous that there is a growing interest in teaching AI in early childhood education (Sabuncuoglu 2020; Yang 2022; Sanusi et al. 2023). Su and Zhong (2022) discusses the importance of AI literacy at a young age due to the role of AI in society and emphasizes creating a framework for teaching AI concepts, skills, and attitudes to young children. Their study uses the AI4K12[1] framework and its "Five Big Ideas" as a guide to shaping the curriculum for young learners. Moreover, there has been an increased focus on integrating AI education into fields beyond traditional computing (Thurzo et al. 2023; Wood, Ange, and Miller 2021; Xu and Babaian 2021).

Curriculum Pathway in CS

Prerequisites are critical in determining student progression through a curriculum, especially in CS. Valstar, Griswold, and Porter (2019) found that students' incoming proficiency with prerequisite knowledge significantly correlates with their performance in an upper-division data structures class. Furthermore, Krause-Levy et al. (2023) found that from the instructor's standpoint, prerequisites enable them to assume a baseline of student knowledge, with some caveats.

Moreover, methods have been introduced to redesign prerequisites to reduce entry barriers in CS (Das and Fulton 2024). For instance, Li and Liu (2022) addresses ML prerequisites by suggesting integrating foundational ML concepts into introductory courses like programming and DS. Earlier integration of ML courses is further supported by de Freitas and Weingart (2021), Hu and Hu (2021), and Sahu, Ayotte, and Banavar (2021). In addition, Janeja et al. (2024) highlights how DS courses can be adapted to fit different student populations and institutional frameworks.

Previous work in US *AI* Curriculum Pathway

Our previous work analyzed *AI* courses and the structure of their prerequisites (Niousha et al. 2024). We sampled 50 US R1 institutions to analyze the prerequisite structures of *AI* courses. We first collected the AI, ML, and DS courses within each sampled university and for each course type, we collected course name, level, immediate prerequisites, and offering frequency. Course levels were defined as "Introductory", "Intermediate", "Advanced", or "Cross-listed" (open to both undergraduate and graduate students) which were later coded as levels 1 to 4. The course levels were identified according to each university's course numbering scheme reflecting the complexity of the course content. Offering frequency was categorized into "More than once a year", "Once a year", or "Less than once a year", based on the universities' academic schedules. We found diversity in curriculum frameworks across these institutions: public universities tended to offer more advanced courses with higher prerequisite demands, whereas private institutions provided earlier access to AI and ML courses with fewer prerequisites.

This work introduced the **exposure level** of a course, defined to be the depth of the prerequisite graph, and describes to the earliest possible term that a student can take the *AI* course (assuming optimal course selection). For example, a course (e.g., Data Structures) with an exposure level of 2 might require two sequential prerequisites, such as CS1 $\rightarrow$ CS2 $\rightarrow$ Data Structures. Alternatively, the same course with the same exposure level of 2 could have parallel prerequisites, where a student takes CS1 in the first semester, then CS2 and Linear Algebra concurrently in the second semester, followed by Data Structures in the third semester. We found that DS courses generally required fewer prerequisites compared to AI and ML courses and had lower exposure levels.

Cross-country Comparison

We are interested in validating and expanding the applicability of our framework in new contexts. Canada offers a unique yet comparable academic environment. For example, both Canada and the US recognize the important role of universities in their research and innovation ecosystems with a heavy reliance on government research funding and active university-to-industry collaboration (Bégin-Caouette et al. 2021). On the other hand, Canada's doctoral graduation rates fall behind those of the US, and Bégin-Caouette et al. (2021) suggest this difference could impact Canada's long-term research capacity.

In the context of curriculum research, while there has been some analysis of Canadian university curricula in fields such as Civil Engineering and medicine (Ebadi et al. 2020; Pucchio et al. 2022), to the best of our knowledge, there is limited work on curriculum analysis for CS and specifically AI education in Canadian universities.

Comparing curricula across countries allows us to learn best practices from different educational cultures. However, the literature review revealed that such analyses are limited, especially for AI curricula. By applying our previous framework used on US universities to Canadian universities, we aim not only to understand the Canadian context but also to compare it with the US to identify best practices. This comparison explores how different approaches shape access to *AI* courses to inform global education strategies.

Method

RQ1 Our method for analyzing the prerequisite approaches of Canadian institutions followed that of our previous work Niousha et al. (2024).We sampled 30 universities from a list of 104 Canadian universities, obtained from

[1]https://ai4k12.org/

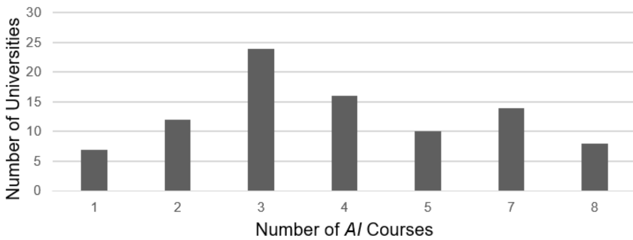


Figure 1: Histogram of the number of *AI* courses per university in Canada.

the Employment and Social Development Canada website[2]. From the 104 universities, we excluded universities without a CS department and without any *AI* courses. 54 universities fit these criteria, from which we sampled 30 universities.

We then studied the academic calendar of the CS department to obtain all courses offered by the department. Based on the course description on the websites, we identified and categorized *AI* courses by examining the course syllabi. Additionally, we verified whether the course is currently offered by checking the course's offering status in the latest posted academic calendar. We collected 91 *AI* courses total, including 36 AI, 39 ML, and 16 DS courses. Figure 1 shows the histogram of the number of *AI* offered per university.

We used each university's course calendar to identify the entire prerequisite sequence for each *AI* course. For coding the prerequisites, we began by using the codebook developed in (Niousha et al. 2024), with two coders initially collaboratively coding 26 courses (80 prerequisites); two additional codes were added to the codebook to account for the courses "Mathematical Proof" and "Introduction to Math", which are common in Canadian institutions. The former is an introduction to formal proofs (in both discrete and continuous settings), and the latter focuses on pre-calculus content on functions and relations. With the updated codebook in Table 1, the two coders independently coded the prerequisites for 20 courses and obtained an inter-rater reliability of $\kappa = 0.867$ (Cohen's kappa), indicating substantial agreement (McHugh 2012). The remaining 45 courses were then evenly split between the two coders for coding.

Using the prerequisite structure, we computed the *exposure level* of each course. Additionally, we used the prerequisite graph structures of the *AI* courses in a sample to produce a Sankey diagram to visualize the frequent prerequisite paths. Finally, we used the prerequisite data for each course to cluster (using k-means clustering) the Canadian *AI* courses into 8 clusters: the features used for clustering included the course type, course level, total number of prerequisites, and the prerequisite courses, with categorical data represented through one-hot encoding. The optimal k-value was determined by maximizing the silhouette score between 2 and $\sqrt{n/2}$, a heuristic based on the number of data points.

RQ2 To compare the curriculum structure of *AI* courses in the US and Canada, we compared the results from the exposure level, Sankey diagram, and clustering analyses with those in (Niousha et al. 2024).

[2]https://www.canada.ca/en/employment-social-development/programs/designated-schools.html

Category	Code Names
Mathematics	Discrete Mathematics, **Introduction to Math**, Linear Algebra, **Mathematical Proof**, Multi-variable Calculus, Probability, Statistics, Single-variable Calculus
Computing	Architecture and Organization, Artificial Intelligence, CS1, CS2, Data Structures, Data Management, Data Science, ML, Object-oriented Programming, Software Engineering
Others	"Society, Ethics and Professionalism", Signal Processing

Table 1: Updated codebook. New codes are shown in bold.

RQ3 To demonstrate ways institutions can lower the exposure of *AI* courses, we analyzed specific approaches institutions are taking by drawing examples from universities that offer low exposure *AI* courses. First, we defined the very low exposure *AI* courses. These include non-technical introductory courses (e.g., history of AI, AI ethics, etc.). Then, we analyzed only *intermediate* course level *AI* courses in order to avoid non-technical courses and avoid courses with "hidden prerequisites" that are not actually accessible to early undergraduate students.

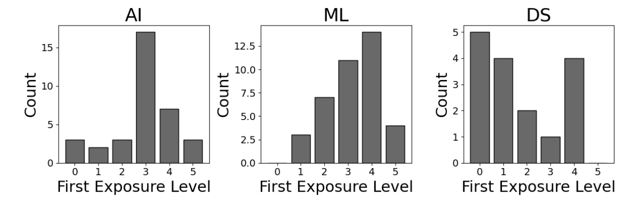
For the latter analysis, for each course type (AI, ML, or DS), we selected the *intermediate* courses with the lowest exposure level within the filtered sample to show as an example course that allows early exposure. However, we excluded courses with exposure level 0 since the structure is not demonstrative. Moreover, courses with prerequisite structures that significantly differed from the Sankey diagram were considered outliers and were excluded.

Results

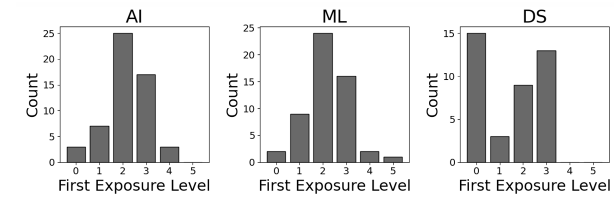
RQ1: Prerequisites Structures within Canadian Universities

Exposure Level. Figure 2a shows the exposure level for *AI* courses in Canadian universities. Most AI courses had an exposure level of 3, indicating that 3 semesters are required before students can take these courses. ML courses generally had higher exposure levels. DS courses' exposure levels had a wider distribution, with many accessible in year 1.

Prerequisite Chain. Figure 3a visualizes the common prerequisite links in *AI* courses in Canadian universities as a Sankey diagram. This figure explains some of the patterns we saw in Figure 2a. For example, Figure 3a verifies that Canadian DS courses had lower exposure levels compared to AI and ML courses, illustrated by the small number of edges linked to the DS node. Moreover, the high-exposure



(a) Histogram of the exposure levels of Canadian *AI* courses.



(b) Histogram of the exposure levels of US *AI* courses, from Niousha et al. (2024).

Figure 2: Comparison of first exposure levels in the Canadian (a) and US (b) curricula.

DS courses were likely those with a Statistics prerequisite, which itself requires previous math or probability courses.

Figure 3a also shows that AI and ML have more advanced prerequisites. In fact, CS1, CS2, and Data Structures were the three most common courses in the prerequisite chains for AI and ML courses. Canadian AI courses in our sample were quite homogenous in their prerequisites, with 26 AI courses (72%) in our sample requiring Data Structures. Data Structures itself can be a high-exposure course—starting from CS1 to CS2 to OOP, and also sometimes including Mathematical Proofs and Discrete Math in the prerequisite chain. Prerequisites for ML courses were more varied. Generally, ML courses require both CS prerequisites (e.g., Data Structures, AI, or Software Engineering) and math prerequisites (e.g., Linear Algebra, Probability, Statistics).

Clustering. We performed K-means clustering on the course prerequisite structure and found the following 8 clusters, also shown in Figure 4:

1. AI courses, advanced level, common prerequisites include Data Structures and CS2 ($N = 28$).
2. Advanced level courses, frequently appeared prerequisites include Multi-variable calculus, Linear Algebra, and Single variable calculus ($N = 11$).
3. Advanced ML courses, the low number of immediate prerequisites includes Data Management ($N = 7$).
4. DS courses at an introductory level have few immediate prerequisites ($N = 11$).
5. ML courses, advanced level, common prerequisites include CS2 and Data Structures($N = 17$).
6. Intermediate Level DS courses, common prerequisites include CS1 and Data management ($N = 7$).
7. ML courses, advanced level, high total number of prerequisites include Linear Algebra and ML(pre) ($N = 5$).
8. AI course, advanced level, common prerequisites include Multi-variable calculus and Object Oriented Programming (OOP) ($N = 5$).

RQ2: Differences in Structure Prerequisites of *AI* Courses Between US and Canada

Comparison of the exposure level. Figure 2 shows that there are differences in exposure levels of *AI* courses in Canada and the US. Overall, the exposure levels of these courses leaned *higher* in Canada compared to the US. For example, the most common exposure levels for US AI and ML courses were 2, whereas in Canada these values were higher at exposure level 3 for AI courses and 4 for ML courses. The difference can be seen in Figure 3 and is discussed in the next section. There were also fairly low variances in AI course exposure levels and a larger variance in ML course exposure levels in Canada.

The exposure level pattern for DS courses also differed in Canada. First, the percentage of DS courses in our sample was lower than in the US, suggesting that computing departments in Canada offered fewer DS courses in general. Although, like in the US, many DS courses did not have prerequisites, Canadian institutions also offered high-exposure level DS courses that we did not see in US institutions.

Comparison of the Prerequisites. Figure 3 shows the Sankey diagrams of the prerequisites of *AI* courses in Canada and the US. These diagrams show distinct differences not on the *AI* prerequisites, but how CS and math prerequisites are structured differently more generally in Canadian and US institutions.

For example, we found that US universities usually use OOP as an introductory first-year course, while Canadian universities tend to enhance the understanding and application of programming languages through such courses only after students have taken CS1 or CS2.

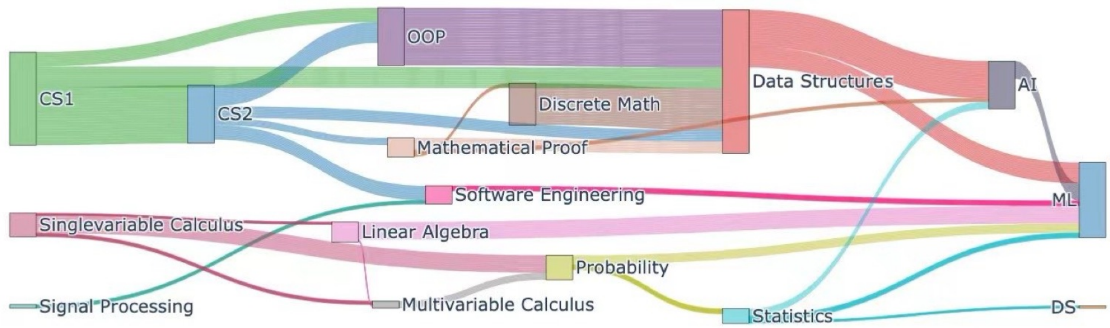
Another difference is that our sample showed that Canadian universities typically required introductory Mathematical proof courses in the freshman year (about 26 courses in the sample) to provide a foundation for subsequent advanced *AI* courses that cover introductory mathematical proofs and mathematical induction. In contrast, US universities did not offer such courses, instead integrating relevant content into Discrete Mathematics or Data Structures courses.

The prerequisites for DS courses in Canada were more homogeneous than in the US, with the Sankey diagram showing a single edge from Statistics to DS course. In contrast, in US institutions, DS courses can have a wider range of prerequisites like Data Structures, CS2, and Data Management.

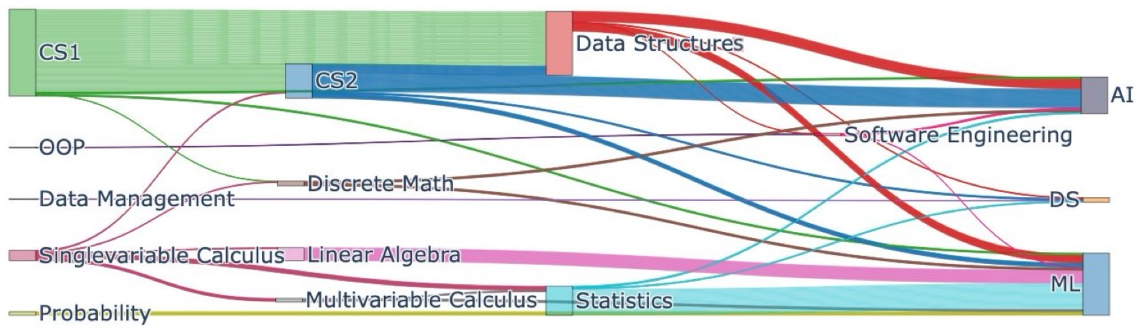
Finally, Canadian universities more often use AI courses as a prerequisite for ML courses, indicated by edges from AI to ML courses. These ML courses tend to be more advanced ML courses, (e.g., covering topics like deep learning and natural language processing).

Despite these differences, there are also similarities between Canadian and US universities. For instance, both ML and AI generally require foundational programming courses (i.e., CS1 or CS2). In addition, AI emphasized more programming-related courses such as OOP and Data Structures, while ML focused more on math courses like Linear Algebra and Calculus.

Comparison of the Clusters. Comparing the course clusters of Canada against the US clusters identified in our pre-



(a) Sankey diagram representing prerequisite chains of Canadian *AI* courses



(b) Sankey diagram representing prerequisite chains of US *AI* courses, from Niousha et al. (2024)

Figure 3: Comparison of prerequisite chains for *AI* courses in Canadian (a) and US (b) universities. The nodes represent prerequisite courses, and the lines connecting each node represent the relationships. For example, if one university's AI course has its CS2 course as a prerequisite, which in turn has CS1 as a prerequisite, two lines would be plotted connecting CS1 to CS2 and CS2 to AI (from left to right). The width of a connection between two nodes corresponds with the frequency of that particular prerequisite relationship. For (a) connections that occur less than 3 times are not plotted for graph clarity.

vious work, we found that both Canada and the US offered advanced AI and ML courses that typically require CS2 and foundational math courses like Linear Algebra and Probability. Also, both countries provided introductory DS courses with few prerequisites, making them accessible to early-stage students. Moreover, in both Canada and the US, ML courses showed variations in prerequisite levels, with some requiring minimal preparation and others demanding a stronger mathematical background.

RQ3: Approaches for Early Exposure to *AI*

In this section, we demonstrate approaches that institutions take to allow students to start *AI* courses earlier in their academic journey and without requiring extensive preparatory work. To do so, we analyzed two types of low exposure *AI* courses: (1) courses intended to introduce students to some *AI* concepts, but may not cover all the content typical in rigorous *AI* courses (e.g., align with the CSC2023 curricular guidelines for AI/ML courses), (2) *intermediate* level courses that cover major topics in *AI* and require advanced prerequisites, but with prerequisites structured in ways to make sure these courses are accessible early on. Both of these approaches align with ways that make *AI* accessible.

Low Exposure *AI* Courses In this section, we highlight our sample's lowest exposure courses in AI and ML. These courses provide avenues for early exposure and draw students' interest towards *AI*. DS courses with low exposure levels were not atypical, so their discussion is omitted.

There were five AI courses with exposure level 0 in our samples, 3 from Canada and 2 from the US: "Special Topics in Artificial Intelligence", "Philosophy of Artificial Intelligence", "Artificial Intelligence Everywhere", "Concepts in Artificial Intelligence", and "Demystifying Artificial Intelligence". The first course is an example of an upper-level course with no formal prerequisites, but which may not be accessible to novice students. Most of the other courses were interdisciplinary courses that discuss the history, nature, limits, and societal impact of AI. The last course was "designed for students that want to learn about AI and machine learning but don't have the course schedule bandwidth to build up the math and computing background".

There were three ML courses with exposure level 1 in our

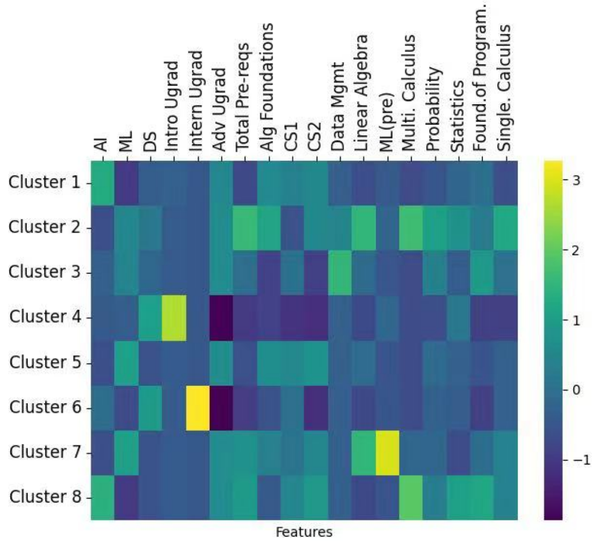


Figure 4: Heatmap of cluster centers k-means on courses. Each column represents a feature (course type, level, frequency, number of prerequisites, prerequisite courses).

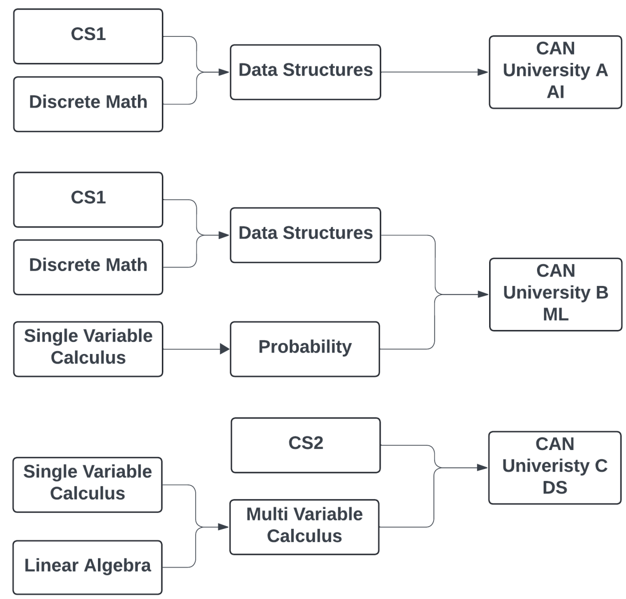


Figure 5: Prerequisites of intermediate *AI* courses in Canada.

sample: “Machine Learning”, “Deep Learning”, and “Basics of Machine Learning”. Again, the first two courses may not be accessible to novice students. However, the latter course intended to “provide a solid foundation in the mathematics of ML, in preparation for more advanced ML concepts.” We thus identified consolidating the math prerequisites as a strategy for introducing ML earlier in the curriculum. In our US sample, there are 10 ML courses with exposure level 0 or 1. Again, many of these were advanced courses that may have hidden prerequisites and are not accessible to novices. Some of these courses had titles such as “Applied Machine Learning” and taught ML with little math.

Rigorous *AI* Courses Although introductory *AI* courses can provide early exposure to key *AI* topics, access to advanced *AI* courses covering technical content rigorously is still important for undergraduate CS students. This section discusses how the exposure level of such courses has been successfully reduced in Canadian and US institutions. Specifically, we focus on *AI* courses at the *intermediate* course level. Figure 5 and Figure 6 provides examples of such courses with lower exposure than usual.

In Canada, there were 13 **AI courses** at the *intermediate level*, all of which had the course titles similar to “Artificial Intelligence” or “Introduction to AI”. One course had an exposure level of 2, shown in Figure 5. This course required Data Structures as a prerequisite, which itself requires CS1 and Discrete Math. There were 9 *intermediate* **ML courses**, most of which had the course title “Machine Learning”, but two courses had titles “Deep Learning” and “Reinforcement Learning” (RL). Two of these courses had exposure level 2, including the RL course. We selected the non-RL course to explore in Figure 5. The prerequisites required for this course follow Figure 3a: however, the prerequisite courses were structured in a parallelizable way, so that a strong student can take multiple prerequisites simultaneously to access this course earlier. Finally, there were 2 *intermediate* **DS courses**, with exposure levels 2 and 4. The latter course had two *introductory* DS courses as prerequisites. We show the remaining course prerequisites in Figure 3a.

In the US, there were 4 *intermediate* **AI courses**, with exposure levels 0 to 3, all with similar titles as the Canadian counterparts. The minimum exposure level courses either had no prerequisites or only a CS1 prerequisite, shown in Figure 6. There were 6 *intermediate* **ML courses**, titled either “Machine Learning”, “Elements of Machine Learning” or “Applied Machine Learning”. One course required only single-variable calculus and had little other information publicly available. The remaining courses all had exposure level 2. Like the Canadian counterparts, the prerequisite structure of this course is highly parallelizable, allowing many prerequisite requirements but a low exposure level. Finally, for intermediate **DS courses**, there were 6 in total, with a range of exposure levels (2 courses with level 0, 1 with level 1, etc.). The course with exposure level 1 required only CS1. The course with exposure level 2 is shown in Figure 6.

Discussion

Early Accessibility of DS Courses

Our RQ1 results show that DS courses were generally more accessible than AI and ML courses in Canadian institutions. This finding aligns with our previous research in US R1 institutions (Niousha et al. 2024). This approach leverages DS courses as an entry point for introducing AI and ML concepts early in undergraduate education to ensure broader accessibility for students and is also proposed in Spector (2024).

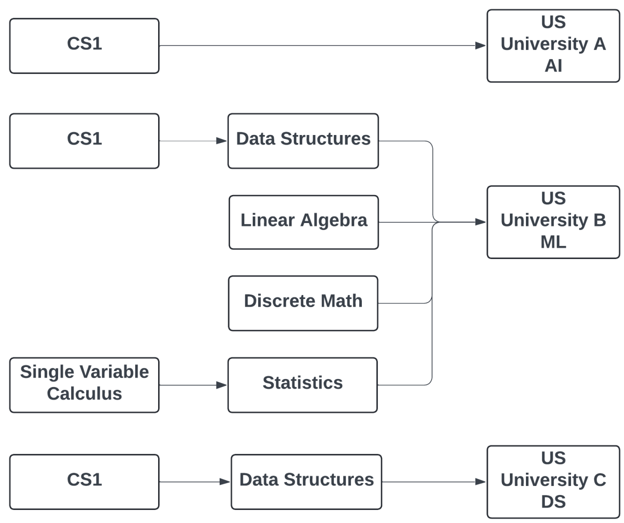


Figure 6: Prerequisites of intermediate *AI* courses in the US.

Higher Exposure Levels for *AI* Courses in Canada Compared to US

Our analysis from RQ2 showed that *AI* courses in Canada generally have higher exposure levels than in the US, meaning Canadian students start engaging with these courses later in their academic careers. Taking *AI* courses later can reduce the remaining time for advanced study, participation in research, and obtaining internships that apply skills developed in these courses. This challenge aligns with findings from Valstar, Griswold, and Porter (2019), highlighting the importance of reducing delays caused by prerequisite structures to enhance student readiness for advanced topics. There is an opportunity in Canadian institutions to find ways to introduce *AI* topics earlier in the curriculum.

Innovative Approaches to Introduce *AI* Earlier

In RQ3, we found that institutions in the US and Canada alike adopted innovative approaches to enable students to engage with *AI* courses earlier. One approach is to offer introductory *AI* courses with little to no prerequisites. These can be interdisciplinary courses on the history and philosophy of *AI*, or introductory courses on applied AI. Another approach is to offer courses that teach the prerequisites alongside some of the *AI* content, as also suggested in Li and Liu (2022). The goal and impact of these approaches vary: e.g., sparking interest in *AI*, broadening participation in *AI* as in Barretto et al. (2021), versus lowering the barrier for obtaining technical *AI* skills.

Parallelizing Prerequisites and Academic Advising

In the second part of RQ3, by studying low-exposure-level AI and ML courses, we found that parallelizing course prerequisites can allow students to enter these fields earlier. The successful examples we listed achieved this by parallelizing necessary CS and mathematics prerequisites, allowing students to take these courses simultaneously. This reduces the delay in entering AI and ML courses and enables students to engage with these advanced courses more quickly.

However, first-year students may lack proper academic planning, where academic advising is crucial. Academic advisors help students plan their learning pathways, ensuring they complete the necessary prerequisites early in their academic careers. With effective guidance, students can take these courses at the optimal time, avoiding delays due to poor course scheduling. Therefore, combining academic advising and parallelizing prerequisites is essential to ensure students successfully enter the AI and ML fields.

Limitation

We analyzed publicly accessible course information, which was potentially incomplete or outdated. Course calendar information often did not specify all prerequisites or whether prerequisites were strictly enforced. Differences in the way institutions in Canada versus the US encoded and updated their calendar information may have contributed to some of the differences we observed. Moreover, we only considered courses offered by CS departments and did not collect data on *AI* courses offered in Statistics and Mathematics departments, or *AI* courses offered in disciplinary contexts. This likely impacted the interpretation of data on DS courses; for example, DS courses may have been offered in different departments in Canada compared to the US.

Higher education in Quebec differed from the system in other Canadian provinces, with an additional year of study required before students entered university. Thus, we likely *underestimated* the exposure levels of Quebec *AI* courses.

We could not replicate all analyses in (Niousha et al. 2024), including course offering frequency and public vs. private institution comparisons, due to limited publicly available data on course frequency and the small number of private universities in Canada (only one in our sample). Additionally, we used fewer features in our clustering analysis, making the clustering comparison approximate. We also did not analyze advising differences between US and Canadian institutions, which may affect parallel prerequisite structures.

Conclusion

This study analyzed the curriculum structure of *AI* courses in Canada and compared it to the US. Canadian CS departments offered fewer DS courses and had longer prerequisite chains for AI and ML, with more ML courses requiring AI. To introduce *AI* earlier, we suggest offering DS, introductory AI, and applied ML courses with fewer prerequisites, and parallelizing prerequisites. The study highlights curricular diversity in North America and recommends revisions and early advising to improve AI course access.

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