Artificial Intelligence Curricula: Comparative Prerequisite Pathways Analysis in North America

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by

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Committee in charge:

Professor Narges Norouzi, Research Advisor
Professor Lisa Yan, Second Reader

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Research Project

Submitted to the Department of Electrical Engineering and Computer Sciences, University of California at Berkeley, in partial satisfaction of the requirements for the degree of **Master of Science, Plan II**.

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Abstract

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This work examines Artificial Intelligence (AI), Machine Learning (ML), and Data Science (DS) courses in North America, focusing on the accessibility of the courses to learners of different academic backgrounds. Analyzing 50 US and 30 Canadian universities, it identifies key differences in course pathways. DS courses generally have lower entry requirements, while AI and ML courses in both countries often demand extensive prerequisites. US institutions typically provide earlier access to AI, ML, and DS courses with more flexible prerequisites, whereas Canadian universities emphasize more layered preparation, delaying student exposure. To improve accessibility, the study highlights several strategies such as parallelizing prerequisites, integrating foundational content into introductory courses, and offering low-barrier interdisciplinary courses to engage students early. The thesis introduces a codebook and exposure-level metric to systematically analyze and compare curricula across different institutions. These findings provide actionable recommendations to make AI in Higher Education more accessible and prepare a diverse range of students for opportunities in this rapidly growing field.

Contents

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Chapter 1

Introduction

1.1 Advancement in AI and Influence in CS Education

The rapid advancement of Artificial Intelligence (AI) has profoundly impacted various industries [1] and their applications across fields such as healthcare, finance, and education [2, 3, 4, 5, 6]. These disciplines have unlocked new opportunities for research, development, and innovation. As AI continues to shape various industries, it has also become critical in preparing future leaders who can tackle complex challenges in these sectors [7, 8, 9].

The increasing ubiquity of AI has naturally made it a central focus of Computer Science (CS) education. The design of university AI programs has significant implications for shaping the future workforce and fostering innovation [10]. Specifically, the AI-related courses in the CS department AI, Machine Learning (ML), and Data Science (DS) (hereafter referred to as *AI in Higher Education* (*AIHD*) courses) have been introduced with great effect in higher education, particularly in areas such as academic performance prediction and employability enhancement [11]. The integration of *AIHD* courses into CS curricula has gained prominence, with universities striving to equip students with the skills needed to navigate and lead in an AI-driven world.

However, despite their growing significance, *AIHD* courses face several challenges. Diversity remains a pressing issue, with systemic barriers limiting access for underrepresented groups in the field [12, 13]. Additionally, these courses are reported to be particularly challenging for both students and instructors due to their interdisciplinary nature and steep learning curve [14, 8, 15]. This difficulty is exacerbated by the complex prerequisites required for most *AIHD* courses. A strong foundation in mathematics including calculus, linear algebra, and probability as well as advanced programming skills, is often essential for success [16, 17, 18, 19].

Such requirements create significant barriers for many students, particularly those from non-traditional or less privileged educational backgrounds. These barriers have also led some CS educators to become hesitant in introducing *AIHD* courses to non-majors, further limiting "accessibility" (in this report, this word is used as the accessibility of the courses to learners of different academic backgrounds) and early exposure to these critical subjects [20]. Yet, introducing accessible and engaging *AIHD* curricula at earlier stages is essential to motivate the next generation of learners and ensure that students from all backgrounds can contribute meaningfully to the field [21, 22, 23]. Addressing these challenges will require innovative prerequisite pathways that balance rigor with accessibility.

1.2 Motivation

This report is motivated by the need to evaluate how undergraduate curricula prepare students for AI careers by fostering technical understanding, application understanding, and eventually research skills. While *AIHD* courses have gained prominence in higher education, many institutions are still in the early stages of integrating these fields into their curricula [11]. This highlights the need to analyze how curricula are structured to introduce *AIHD* courses effectively. Graduate courses are excluded from this analysis because they are specialized and cater to a narrower audience. By focusing on the accessibility and prerequisite structures of undergraduate *AIHD* courses, this study seeks to identify the earliest point a student can engage in such courses and optimize pathways, ensuring they are well-prepared for careers in these transformative fields.

1.3 Research Questions and Contribution

Rethinking traditional prerequisite pathways and exploring innovative approaches enables educational institutions to empower students to engage with *AIHD* courses. This shift not only helps demystify the field for beginners but also ensures that students from varied academic and demographic backgrounds are better positioned to contribute to these domains. Addressing these challenges requires a systematic investigation into current curricular practices, identifying bottlenecks in prerequisite structures, and proposing actionable solutions to make *AIHD* courses more accessible. Hence, this thesis addresses the following Research Questions (RQs):

- **RQ1**: What approaches are institutions using to structure prerequisites for *AIHD* courses in R1 CS departments in the United States (US)?
- **RQ2**: What approaches are institutions using to structure prerequisites for *AIHD* courses in CS departments in Canada?
- **RQ3**: What are the similarities and differences in the prerequisite structure of *AIHD* courses between the US and Canada?
- **RQ4**: What approaches can institutions use to allow early exposure to *AIHD* courses for undergraduate students in the US and Canada?

By comparing US and Canadian institutions, this work highlights differences, similarities, and transferable practices to enhance student engagement and access. Canada was chosen to apply the framework used for US institutions due to its similar academic structures while differences enrich the comparative analysis. The aim is to propose actionable strategies for fostering earlier and more inclusive exposure to *AIHD* courses. Through analyzing and identifying bottlenecks, this work provides a framework for designing accessible and inclusive AI education for students.

This report makes three key contributions to AI education. First, it introduces a comprehensive codebook for categorizing prerequisites in *AIHD* curricula. The codebook standardizes the various prerequisites for *AIHD* courses offered across universities, allowing researchers to systematically analyze and compare course structures and identify gaps. Second, it develops a metric, *first exposure* level, to quantify how early a student can take an *AIHD* course in their academic career. This metric provides a way to assess the accessibility of *AIHD* courses by calculating the depth of the prerequisite tree of a course. Third, it combines the codebook and the *first exposure* level into a comparative framework for evaluating *AIHD* curricula across institutions and countries. This framework helps institutions assess their programs, benchmark against other institutions, and identify barriers to accessibility. It also highlights strategies for providing earlier exposure to *AIHD* courses and reducing entry barriers for students. Together, these contributions aim to create more accessible pathways in *AIHD* education.

1.4 Overview

In the following chapters, this report systematically addresses its research questions. Chapter 2 reviews key literature on curriculum pathways, challenges in AI education, and cross-country comparisons, identifying gaps this study aims to fill. Chapter 3 describes the two-phase research approach, focusing on US institutions and Canadian universities, and details the coding and analytical frameworks used. Chapter 4 present findings on prerequisite structures and strategies for fostering early exposure to *AIHD* courses. Chapter 5 interprets the findings, explores their implications for curriculum design and policy, acknowledges the study's constraints, and outlines directions for future work. Finally, Chapter 6 summarizes the report's contributions.

Chapter 2

Related Work

2.1 History of Computer Science Education Curriculum Development

CS is a rapidly growing discipline, and constant curriculum design updates have been an integral part of its education history to balance foundational knowledge with the demands of emerging technologies [24]. The origins of CS education can be traced back to the late 1960s and early 1970s when foundational efforts were primarily focused on the psychology of programming. This included understanding how novices transition into experts and identifying the challenges faced by beginners in learning programming [25]. During this period, educational tools like the Logo programming language emerged, designed to teach critical thinking and mathematical reasoning through programming, setting the stage for integrating computing concepts into broader educational contexts.

By the 1990s, there was a pedagogical shift in CS education, as educators recognized the importance of moving beyond rote learning to foster deeper understanding. Ben-Ari [26] advocated for constructivist teaching methods that emphasized active learning, encouraging students to engage directly with the material to construct their understanding. This shift reflected a growing awareness of the need for more student-centered teaching approaches in CS education.

As the field progressed into the 2000s, the focus expanded to include practical skills such as software testing, an area that was often underemphasized in traditional curricula. Edwards [27] highlighted the importance of teaching students reflective learning practices through software testing methodologies, which not only improved problem-solving skills but also prepared students for real-world software development challenges. These milestones illustrate how CS education has continually evolved and adapted to changing educational needs.

2.2 Curriculum Pathway in Computing Education

Prerequisites are critical in determining student progression through a curriculum, especially in CS [28, 29]. Students' incoming proficiency with prerequisite knowledge significantly correlates with their performance in an upper-division data structures class [30]. From the instructor's standpoint, prerequisites enable them to assume a baseline of student knowledge, with some caveats [31]. While prerequisites simplify course design, they can also discourage or delay students from enrolling [32]. Several methods have been introduced to redesign prerequisites to reduce entry barriers in CS [33]. For instance, Brodley, Quam, and Weiss [34] analyzed the math requirements of CS degrees across US universities, providing recommendations for CS departments to consider to improve access, retention, and on-time degree completion. Moreover, Song [35] showed that micro-credentials can help instructors identify key skills and learning outcomes, potentially reducing entry barriers by breaking down complex prerequisites into more manageable components.

Furthermore, earlier works demonstrate that *AIHD* can be taught without extensive technical prerequisites. Li and Liu [36] addresses ML prerequisites by suggesting integrating foundational ML concepts into introductory courses like programming and DS. This approach aims to make ML concepts more accessible by reducing the intimidation factor for students encountering them for the first time. Earlier integration of ML courses is further supported by Freitas and Weingart [20], Hu and Hu [37], and Sahu, Ayotte, and Banavar [38], who argue that such exposure increases student engagement and prepares them for more specialized topics later in the curriculum. In addition, Janeja et al. [39] highlights how DS courses can be adapted to fit different student populations and institutional frameworks. These adaptations ensure that DS education remains flexible and inclusive, catering to variations in student preparation, institutional priorities, and resource availability.

2.3 Rise of Awareness in Teaching *AIHD*

Teaching *AIHD* at the university level is a well-established topic in CS education [40, 41]. While the popularity of *AIHD* courses is growing, research on best practices for teaching these subjects, which require a strong foundation in both computing and mathematics, remains limited [42].

Apart from the complex theories and knowledge, students may prefer applied AI, focusing on practical problem-solving over complex theories [43]. DS courses are particularly suited to providing these hands-on skills. 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 [44, 45]. Barretto et al. [12] recommends enhancing AI and ML participation by adding courses on their societal and cultural impacts, targeting underrepresented students interested in these broader topics over technical aspects. Allen, McGough, and Devlin [15] advocate combining theoretical and practical teaching methods, tailored support to address students' mathematics anxiety and confidence issues, and adaptive teaching strategies for complex AI concepts to broaden participation.

AI is so ubiquitous that there is a growing interest in teaching AI in early childhood education [46, 47, 48]. Su and Zhong [49] 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 [50] 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 [51, 52, 53]. Furthermore, in a month-long course teaching ML and Natural Language Processing (NLP) to high school students, participants greatly enhanced their understanding of AI, even though they were only introduced to programming as part of the course itself [54].

2.4 *AIHD* Curricula and Research Engagement

Research engagement is a critical component of a strong *AIHD* curriculum, as early exposure to research opportunities helps students apply their coursework knowledge to real-world problems. With the recent technological advancements, interest in conducting AI research has risen dramatically, particularly with undergraduates [55]. However, AI research is often not available to students without prior experience in related coursework. Providing access to *AIHD* courses early empowers students to engage in undergraduate research sooner, which has important implications for retention and academic success.

For instance, Bhattacharyya et al. [56] found that engaging in undergraduate research increased retention and graduation rates. Similarly, the Early Research Scholars Program (ERSP) at UC San Diego showed that participants had higher GPAs, improved retention rates, and a stronger sense of belonging compared to control groups [57]. These findings suggest that early research experiences foster essential academic skills and positive academic identity, which are vital for success. Additionally, the Students Tackling Advanced Research (STAR) Scholars Program at Drexel University found significant learning gains among students, particularly in understanding research work, developing independence, and improving communication abilities [58]. These programs demonstrate how research engagement, when integrated with strong mentoring [59], enhances student success in *AIHD* disciplines. By ensuring that students have access to *AIHD* courses early and supporting their transition into research, institutions can build programs that not only attract students but also retain and prepare them for advanced studies and AI careers.

2.5 Cross-country Comparision

We are interested in validating and expanding the applicability of our framework in new contexts. As mentioned in Section 1.3, 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 [60]. On the other hand, Canada's doctoral graduation rates fall behind those of the US, and Bégin-Caouette et al. [60] 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 [61, 62], to the best of our knowledge, there is limited work on curriculum analysis for CS and specifically *AIHD* education in Canadian universities.

Comparing curricula across countries allows us to learn best practices from different educational cultures. By applying our 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.

Chapter 3

Methodology

The methodology is divided into two phases. Initially, we focused on R1 (Research-1): Doctoral Universities in the US with "Very High Research Activity" from the Carnegie classification[1] (RQ1). We specifically focused on R1 institutions since we wanted to investigate the process and the associated timeline that prepares students for AI research after taking relevant *AIHD* courses. The purpose was to compare and contrast the various curriculum designs in institutions to evaluate student access to *AIHD* courses. This first phase established a baseline for *first exposure* levels and prerequisite chains, identifying common and different practices and informing the comparative framework used in the second phase, which extends the study to Canadian institutions for cross-country insights (RQ2, RQ3, and RQ4).

3.1 Phase 1: US Institutions Study

Data Collection and Sampling

We first randomly sampled 50 R1 universities, including 37 public universities and 13 private universities. To be included in our sample, a university must have a CS department advertised on its website and offer at least one AI, ML, or DS course within the department. Focusing on CS departments ensures consistency and comparability across institutions, as they are the primary units offering AI, ML, and DS courses. This fixed departmental focus also simplified the process of coding and analyzing course structures later in the study. We excluded two universities that did not meet these criteria and resampled them with other universities that satisfied the inclusion requirements. The geographic distribution of our US sample is illustrated in Figure 3.1

We then collected, for each university, a list of undergraduate *AIHD* courses offered by their CS department. First, we identified relevant courses from each university's academic calendar and classified them as AI, ML, or DS based on the 2023 offering guidelines by examining the course syllabi. This process ensured that the selected courses were representative

[1]https://carnegieclassifications.acenet.edu/institutions/

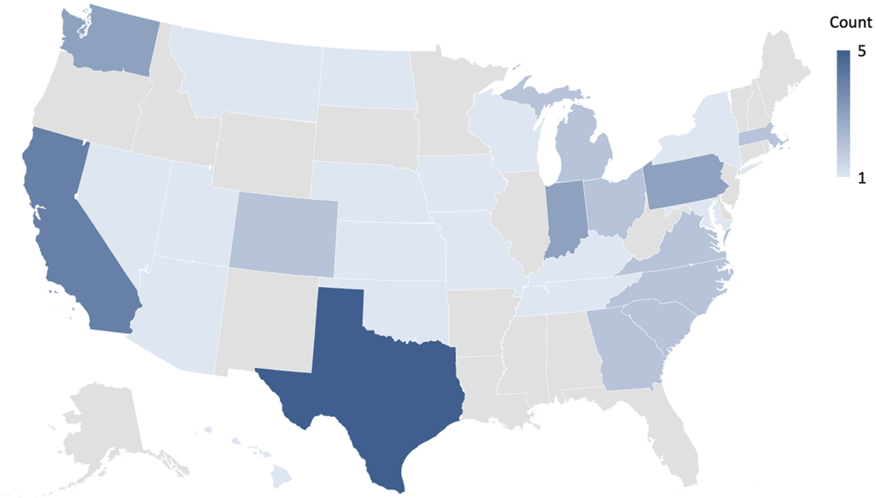


Figure 3.1: US sample of R1 universities.

of their respective subjects. While we considered potential edge cases in categorization, such instances were not prevalent. To maintain relevancy and accuracy, we excluded special topic courses and those that were not recently offered.

We collected information for each relevant undergraduate course, including course type (AI, ML, or DS), course name, level, immediate prerequisites (courses that must be completed directly before enrolling in the course), and offering frequency. Course levels were defined as "Introductory," "Intermediate," "Advanced," or "Cross-listed" (open to both undergraduate and graduate students) 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 ensured data consistency by standardizing the course levels and prerequisites across different universities' terminologies.

Out of our sampled universities, three universities had less than 2 *AIHD* courses, 36 offered between 2 and 3 *AIHD* courses, and 11 universities offered more than 3 *AIHD* courses, as seen in Figure 3.2.

Further, as shown in Table 3.1, our sampled courses included 55 AI, 54 ML, and 40 DS courses. The course level from "Introductory" to "Cross-listed" is coded as levels 1 to 4. AI and DS had a minimum course level of introductory, whereas ML had a minimum intermediate. All three subjects were most often offered at the advanced level.

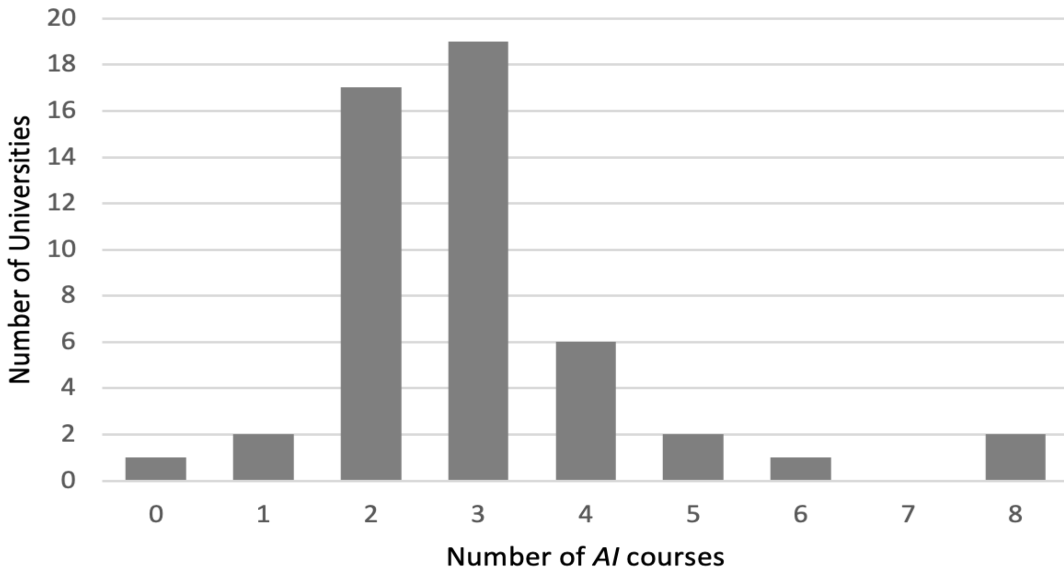


Figure 3.2: Histogram of the number of US *AIHD* courses per university.

Data Analysis Framework

Coding Prerequisites

To structure the diverse set of prerequisites provided by each university, we first gathered information on the immediate prerequisites of each course. Three researchers independently conducted open coding of each course, resulting in three sets of codes. The open coding involved identifying recurring themes and patterns in the prerequisite descriptions, allowing us to generate initial categories. Next, the three sets were merged into a single codebook. During this phase, we held multiple review sessions to discuss and reconcile differences in the codes, ensuring consistency and accuracy. We removed duplicates and aligned our codes with courses provided in ACM's CS Curricula 2023 (Version Gamma)[2]. The course names (codes) in our final codebook is shown in Table 3.2.

Table 3.1: Distribution of Course Levels for *AIHD* Courses in the US.

Course Type	Number of Courses	Average Course Level	Min Course Level	Max Course Level	Mode Course Level
AI	55	2.96	1	4	3
ML	54	3.02	2	4	3
DS	40	2.33	1	4	3

[2]https://csed.acm.org/wp-content/uploads/2023/09/Version-Gamma.pdf

Table 3.2: Categorization of code names.

Category	**Code Names**
Mathematics	Discrete Mathematics, Linear Algebra, Multi-variable Calculus, Probability, Statistics, Single-variable Calculus
Computing	Algorithms, Architecture and Organization, Artificial Intelligence, CS1, CS2, Data Management, Data Science, Machine Learning, Foundations of Programming Languages, Software Engineering
Others	"Society, Ethics and Professionalism," Signal Processing

To enhance reliability, two researchers then coded the prerequisites for each course using the final codebook. There was a 10% overlap in the coding process to check reliability. After this phase, the coders discussed with a third mediator to iterate upon the overlapping codes. Any discrepancies were discussed during this part, and additional modifications were made to the coding, particularly in instances where courses spanned multiple topics. This iterative process achieved high inter-rater reliability, as evidenced by a Cohen's kappa score of 0.95, high substantial agreement [63]. This iterative process ensured that our coding scheme was robust and could be applied uniformly across different institutions.

First Exposure **Level**

To understand when students can first access *AIHD* courses, we focused on identifying the initial entry point for engagement with these courses. Thus, we analyzed the *first exposure* level ($L(c)$) of each course within the prerequisite hierarchy. This metric is defined as follows:

$$L(c) = \begin{cases} 0 & \text{if } c \text{ has no prerequisites (a root node in } G\text{),} \\ \max\{L(c') + 1 \mid (c', c) \in E\} & \text{otherwise.} \end{cases}$$

This approach accounts for both sequential and parallel prerequisites. For example, an AI course with an exposure level of 2 might require two sequential prerequisites, such as CS1 $\rightarrow$ Data Structures $\rightarrow$ AI. Alternatively, an AI course with the same *first exposure* level of 2 could have parallel prerequisites, such as requiring students to complete both CS1 and CS2 before Data Structures and then taking AI. By considering the longest pathway in the prerequisite tree, this metric provides a comprehensive view of course accessibility, capturing the cumulative depth of the prerequisite tree rather than simply the individual course levels.

Common Prerequisite Approach

To understand the common prerequisite approaches, we developed a Sankey diagram (Figure 4.2a) plotting each course's prerequisite chain. We chose this graph to visualize which prerequisites were most often required to determine the most foundational prerequisites for each of the *AIHD* courses. For each of the 50 institutions in our sample, we constructed a prerequisite tree: a directed tree where the nodes are courses needed to take one of the *AIHD* courses, and the edges denote direct prerequisite relation. This approach allowed us to trace each course to its direct and indirect prerequisites.

Clustering Analysis

We used a clustering method (Figure 4.3a) to reveal the characteristics of different institutions and their corresponding courses. Specifically, we analyzed the data using K-means clustering to create course and university clusters. Our features for the course level clustering use five groups of features: Type of course, course level, course frequency, prerequisite statistics, and prerequisite courses using the codebook above. These groups of features were necessary to define how *AIHD* is currently being offered in R1 institutions; taken together, they capture statistics related to access to courses. The course frequency metric in particular offered insights into barriers to access to classes even after prerequisites are completed. Through our analysis, we aimed to highlight the roadblocks students may face to access these courses and, therefore, potential barriers in their pursuit of research opportunities.

For K-means clustering, we used one-hot encoding to represent categorical features. The number of clusters (k) was chosen based on the highest silhouette score between 2 and $\sqrt{\frac{n}{2}}$, a common heuristic to find an optimal k, where n is the number of data points. This resulted in $k = 8$ clusters.

3.2 Phase 2: US vs. Canada Comparison

Data Collection and Sampling

The method for analyzing the prerequisite approaches of Canadian institutions followed that of Phase 1. We sampled 30 universities from a list of 104 Canadian universities, obtained from the Employment and Social Development Canada website[3]. Unlike the U.S., Canada does not officially classify universities into tiers like R1, and it has a much smaller number of universities, making it impractical to restrict the sample to a narrow subset. From the 104 universities, we excluded universities without a CS department and any *AIHD* courses. 54 universities fit these criteria, from which we obtained a sample of 30 universities. The geographic distribution of our Canadian sample is illustrated in Figure 3.3

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

Figure 3.3: Canadian sample of 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 *AIHD* 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 90 *AIHD* courses total, including 36 AI, 38 ML, and 16 DS courses (Table 3.3). Figure 3.4 shows the histogram of the number of *AIHD* offered per university. The average DS course level is 2.3, compared to 3.4 for AI and 3.6 for ML, showing that DS courses have lower *first exposure* levels compared to AI and ML courses. We also collected additional information such as the university name, course calendar URL, and the province where the university is located to replicate the data analyst framework of Phase 1.

Table 3.3: Distribution of Course Levels for *AIHD* Courses in Canada.

Course Type	**Number of Courses**	**Average Course Level**	**Min Course Level**	**Max Course Level**	**Mode Course Level**
AI	36	3.36	1	4	4
ML	38	3.58	1	4	4
DS	16	2.25	1	4	1

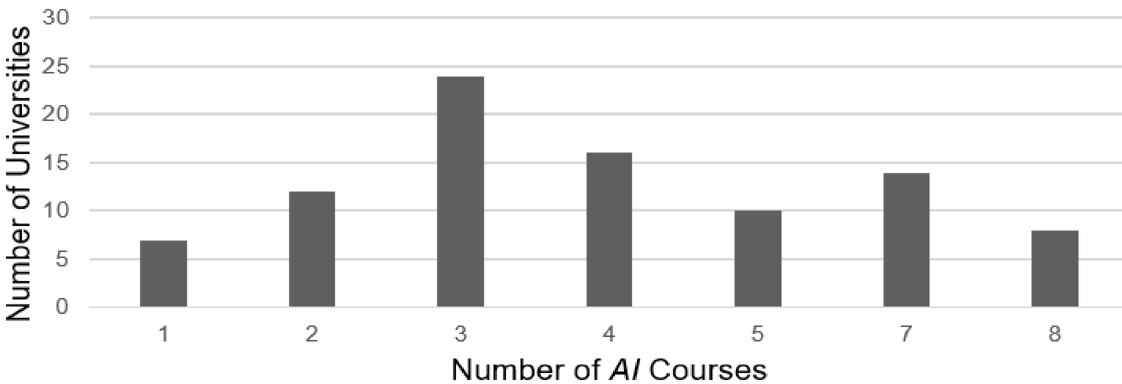


Figure 3.4: Histogram of the number of Canadian *AIHD* courses per university.

Data Analysis Framework

The data analysis framework for Phase 2 is adopted from Phase 1. First, we used each university's course calendar to identify the entire prerequisite sequence for each *AIHD* course. We used the codebook for prerequisite courses developed in Phase 1 (3.2) to code each prerequisite course, with two coders initially collaboratively coding 26 courses (80 prerequisites). At this stage, 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 "Mathematical Proof" course is an introduction to formal proofs (in both discrete and continuous settings), and "Intro to Math" focuses on pre-calculus content on functions and relations. With the updated codebook in Table 3.4 the two coders independently coded the prerequisites for 20 courses and obtained an inter-rater reliability Cohen's kappa score of $\kappa = 0.87$, indicating substantial agreement. The remaining courses were then evenly split between the two coders for coding.

Next, using the prerequisite structure, we computed the *first exposure* level of each course. Additionally, we used the prerequisite graph structures of the *AIHD* courses in a sample to produce a Sankey diagram (Figure 4.2b) to visualize the frequent prerequisite paths. Finally, we used the prerequisite data for each course to cluster (using K-means clustering) the Canadian *AIHD* courses into 8 clusters (Figure 4.3b): 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 the same approach as Phase 2.

Table 3.4: Updated categorization of code names. New codes are shown in bold.

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 Structure, Data Management, Data Science, Machine Learning, Object-oriented Programming, Software Engineering
Others	"Society, Ethics and Professionalism", Signal Processing

Chapter 4

Results

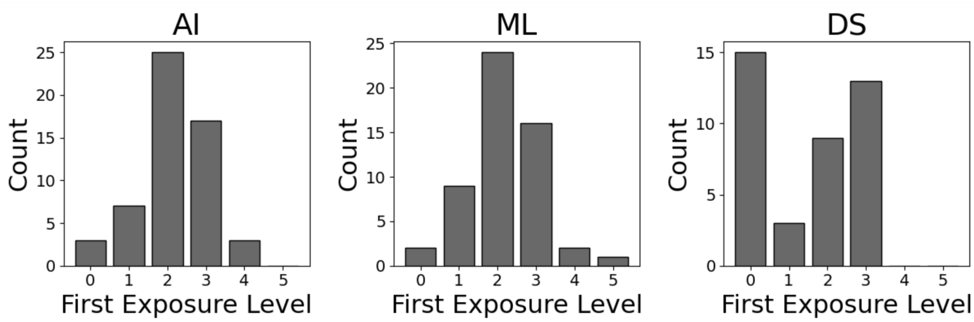
4.1 Approaches in US Institutions (RQ1)

First Exposure Level

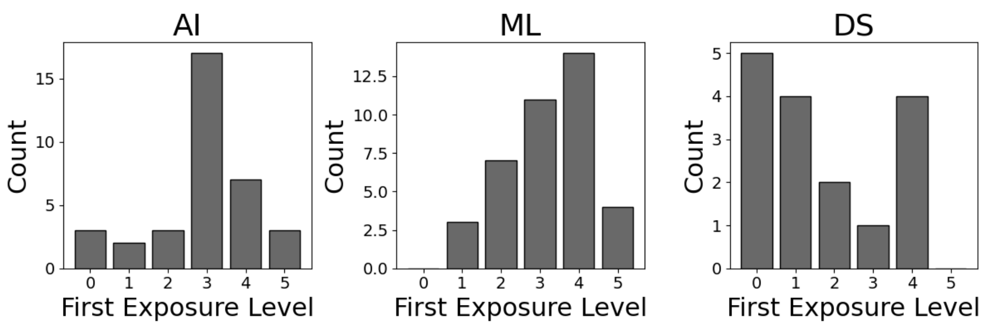
We compared the *first exposure* levels of different course types in the US, as shown in Figure 4.1a. For AI courses, the majority have a *first exposure* level of 2, indicating they are typically encountered after completing foundational prerequisites. Only a small number are available at the *first exposure* level of 1, and none at level 0, indicating a higher entry barrier. ML courses show an even higher entry barrier, with most at the *first exposure* level 2. Some ML courses reach a *first exposure* level of 5, suggesting they require several semesters of prerequisite coursework. DS courses tend to be more introductory, with a significant number having a *first exposure* level of 0, indicating they are available to students in their first semester or year without prerequisites. This early accessibility contrasts sharply with AI and ML courses. These results suggest that DS courses are generally more accessible early in students' academic careers, while AI and ML courses have delayed initial exposure.

Prerequisite Chain

Next, to understand the relationship between prerequisites in US institutions as shown in Figure 4.2a, all prerequisite chains for US courses uses were based on one of the three-course types: CS1 for more programming-related courses and Linear Algebra or Single-variable calculus for more mathematics-related courses. DS courses generally require minimal prerequisites, with only a few universities requiring additional courses like CS2 or Algorithms. In other words, DS courses have fewer and more direct prerequisites, making them more accessible with minimal entry barriers. AI courses typically require a strong programming background, starting from CS1. AI courses also frequently list CS2 and Algorithms as prerequisites, indicating a need for advanced programming and algorithmic knowledge. ML courses require more extensive preparation, often involving long prerequisite chains on both the programming and mathematics sides, starting from CS1 and Single-variable Calculus.



(a) Histogram of the *first exposure* levels of US *AIHD* courses.



(b) Histogram of the *first exposure* levels of Canadian *AIHD* courses.

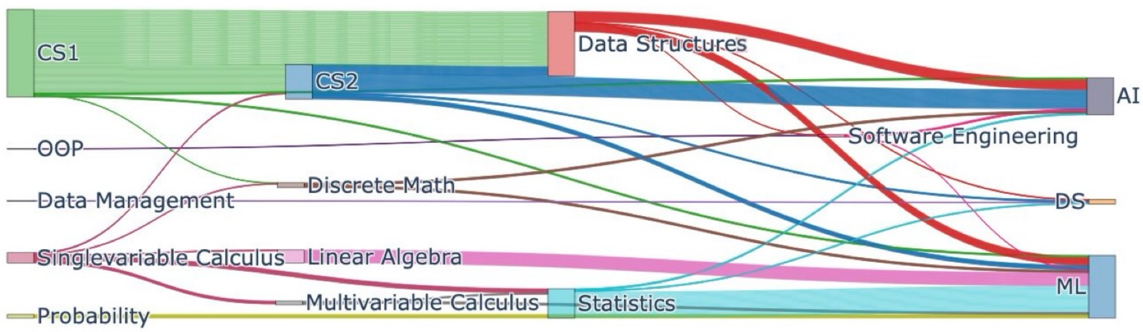
Figure 4.1: Comparison of *first exposure* levels in the US (a) and Canadian (b) curricula.

ML courses exhibit more extensive prerequisite chains, usually beginning with Single-variable Calculus and extending through Linear Algebra, Probability, and Statistics, highlighting the substantial mathematical foundation needed for ML concepts. CS1 is a foundational prerequisite for many AI and ML courses, reflecting the importance of introductory programming skills.

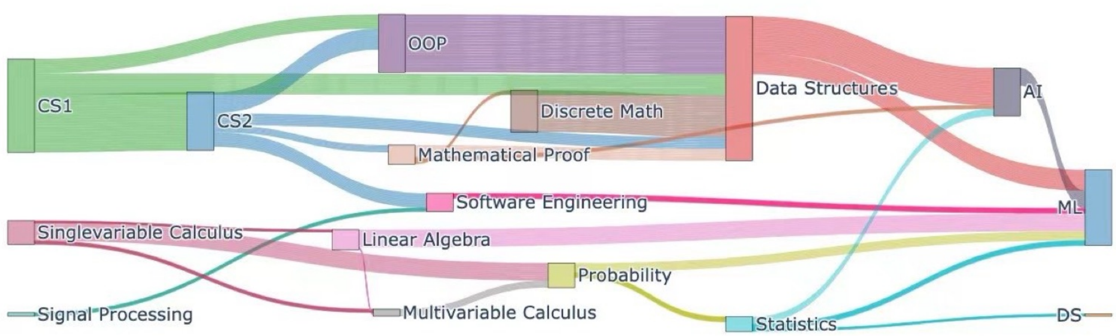
Clustering

To understand the different approaches US institutions use to structure *AIHD* prerequisites, we studied the clustering of different courses offered by the sampled US institutions. Figure 4.3a is a heatmap of the course clusters.

On the x-axis, we have our selected features as described previously, and on the y-axis, we have 8 clusters. The color gradient indicates how important each feature was to the cluster. A lighter shade, such as yellow, indicates that the feature's average value is higher in that cluster than in others. In other words, clusters with lighter shades have a higher importance of that feature compared to clusters with darker shades. For example, the first cluster has a yellow color for AI, which means that its cluster is defined by having AI courses. A darker

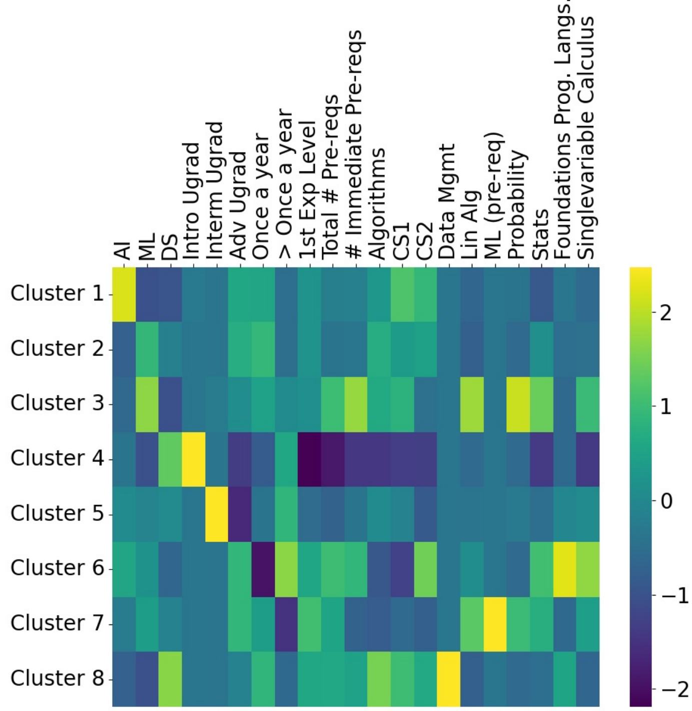


(a) Sankey diagram representing prerequisite chains of US *AIHD* courses.

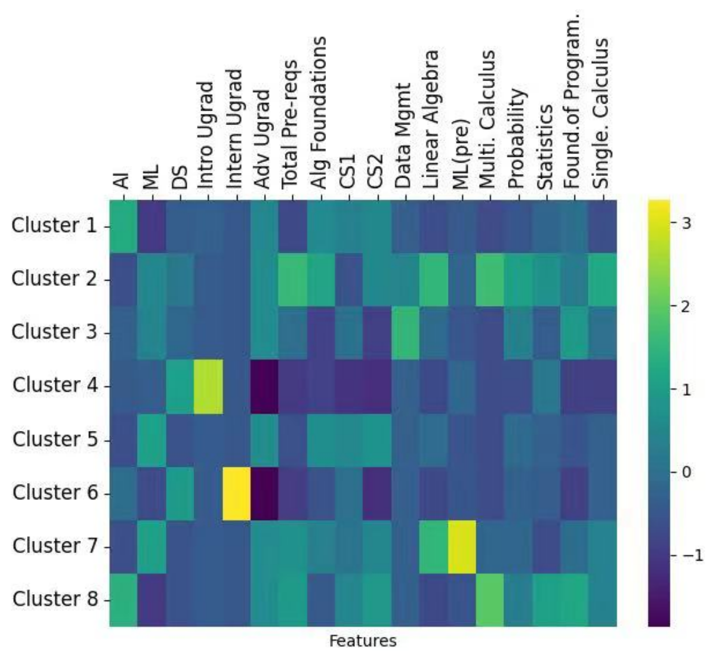


(b) Sankey diagram representing prerequisite chains of Canadian *AIHD* courses.

Figure 4.2: Comparison of prerequisite chains for *AIHD* courses in US (a) and Canadian (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. Connections that occur less than 3 times are not plotted for graph clarity.



(a) Heatmap of course clusters in the US.



(b) Heatmap of course cluster in Canada.

Figure 4.3: Comparison of course-level clusters in the US (a) and Canadian (b) universities. Each column represents a feature (course type, level, frequency, number of prerequisites, prerequisite courses).

shade, such as navy blue, indicates that the feature's average value is lower in that cluster. Notably, the dark blue in Cluster 6 for the "Once a Year" feature suggests that the cluster mainly contains courses not offered once a year. Lastly, the medium-tone colors, such as teal, indicate that a feature was not as relevant to that cluster as to other clusters.

Using these definitions, we find that features including course type, course level, and some prerequisite features help define our clusters, as seen by the light yellows and dark blues in those regions. However, features such as *first exposure* level and number of prerequisites do not define our clusters as much, except for cluster 4, where relatively low prerequisite levels are relevant. The eight clusters have the following characteristics:

1. AI courses, advanced level, offered once a year, common prerequisites include CS1 and CS2 ($N = 45$).
2. ML courses, advanced level, offered once a year, low number of immediate prerequisites, and common prerequisites include CS1 and Algorithms ($N = 31$).
3. ML Courses, advanced level, offered once a year, high level of total and immediate prerequisite courses, and common prerequisites include CS1, Algorithms, Linear Algebra, Probability, Statistics, and Single Variable Calculus ($N = 23$).
4. DS courses at an introductory level ($N = 17$).
5. Intermediate level, offered more than once a year, low *first exposure* levels, low total and immediate numbers of prerequisites ($N = 15$).
6. Advanced level, offered more than once a year, high total number of prerequisites, and common prerequisites include CS2, Statistics, Foundations of Programming Languages, and Single Variable Calculus ($N = 7$).
7. ML courses, advanced level, high *first exposure* level, low number of immediate prerequisites, and common prerequisites include Linear Algebra and Machine Learning ($N = 6$).
8. DS courses, advanced level, offered once a year, and common prerequisites include CS1, CS2 Algorithms, and Data Management ($N = 5$).

4.2 Approaches in Canadian Institutions (RQ2)

First Exposure Level

Figure 4.1b shows the *first exposure* level for *AIHD* courses in Canadian universities. Most AI courses had an *first exposure* level of 3, indicating that 3 semesters are required before students can take these courses. ML courses generally had higher *first exposure* levels. DS courses' *first exposure* levels had a wider distribution, with many accessible in year 1 of the study.

Prerequisite Chain

Figure 4.2b visualizes the common prerequisite links in *AIHD* courses in Canadian universities as a Sankey diagram. This figure explains some of the patterns we saw in Figure 4.1b. For example, Figure 4.2b verifies that Canadian DS courses had lower *first exposure* levels compared to AI and ML courses, illustrated by the small number of edges linked to the DS node. Moreover, the high *first exposure* DS courses were likely those with a Statistics prerequisite, which itself requires previous math or probability courses.

Figure 4.2b also shows that AI and ML have more advanced prerequisites. 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 Structure as a prerequisite. Data Structure 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 Structure, AI, or Software Engineering) and math prerequisites (e.g., Linear Algebra, Probability, Statistics).

Clustering

As a final analysis for RQ2, we performed K-means clustering on the course prerequisite structure and found the following 8 clusters. The following features define each cluster, also shown in Figure 4.3b:

1. AI courses, advanced level, common prerequisites include Data Structure 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 ($N = 10$).
5. ML courses, advanced level, common prerequisites include CS2 and Data Structure ($N = 17$).
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) ($N = 5$).

4.3 Differences and Similarities in US and Canadian *AIHD* Courses (RQ3)

Comparison of *First Exposure* Level

Figure 4.1 shows that there are differences in *first exposure* levels of *AIHD* courses in Canada and the US. Overall, the *first exposure* levels of these courses leaned higher in Canada compared to the US. For example, the most common *first exposure* levels for US AI and ML courses were 2, whereas in Canada these values were higher at *first exposure* level 3 for AI courses and 4 for ML courses. The difference can also be seen in Figure 4.2 and is discussed in the next section. There were fairly low variances in AI course *first exposure* levels and a larger variance in ML course *first exposure* levels in Canada.

The *first 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 CS departments in Canada offered fewer DS courses in general. Like in the US, many DS courses in Canada had no prerequisites, but Canadian institutions also offered high *first exposure* DS courses not found in the US.

Comparison of Prerequisites

Figure 4.2 shows the Sankey diagrams of *AIHD* course prerequisites in Canada and the US. These diagrams highlight not just differences in *AIHD* prerequisites but also in how CS and math prerequisites are generally structured 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 *AIHD* 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 NLP). 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 Clusters

Comparing the course clusters of Canada against the US clusters (Figure 4.3), we found similarities and differences. Both countries offer advanced AI and ML courses that commonly require foundational computing prerequisites such as CS2, Data Structures, and math courses like Linear Algebra and Probability. For example, in the US heatmap, **Cluster 1** represents AI courses with common prerequisites including CS1 and CS2. Similarly, in the Canadian heatmap, **Cluster 1** reflects advanced AI courses, with frequent prerequisites including Data Structures and CS2. Introductory DS courses with few prerequisites are reflected in **Cluster 4** in the US and **Cluster 4** in Canada, making them accessible to early-stage students.

However, variations appear in ML courses: in the US, **Cluster 3** captures advanced ML courses requiring a high total number of prerequisites, including Algorithms, Linear Algebra, Probability, and Calculus. In Canada, **Cluster 7** highlights advanced ML courses with a high total number of prerequisites, including Linear Algebra and Machine Learning. These clusters highlight differences in prerequisite structures across institutions in the two countries.

4.4 Approaches to Allow Early Exposure of *AIHD* Courses (RQ4)

To compare the curriculum structure of *AIHD* courses in the US and Canada, we compared the results from the *first exposure* level, Sankey diagram, and clustering analyses with those in Phase 1.

Best Curricula Practices

After identifying the similarities and differences between US and Canadian Universities in structuring their *AIHD* courses, we wanted to demonstrate ways institutions can lower the exposure of *AIHD* courses. Specifically, we analyzed approaches institutions are taking by drawing examples from universities that offer low-exposure *AIHD* courses. First, we defined the very low *first exposure* level *AIHD* courses. These include non-technical introductory courses (e.g., history of AI, AI ethics, etc.). Then, we analyzed only *intermediate* course level *AIHD* courses in order to avoid non-technical courses and avoid courses with "hidden prerequisites" that have low *first exposure* level but are not actually accessible to early undergraduate students due to prerequisites not officially publicized. For each course type (AI, ML, or DS), we selected the intermediate courses with the lowest *first exposure* level within the filtered sample to show an example course that allows early exposure. However, we excluded courses with *first 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. In this section, we demonstrate approaches that institutions take to allow students to start *AIHD* courses earlier in their academic journey and without requiring extensive preparatory work. To do so, we analyzed two types of low *first exposure AIHD* courses: (1) courses intended to introduce students to some *AIHD* courses, but may not cover all the content typical in rigorous *AIHD* courses (e.g., align with the CSC2023 curricular guidelines for AI and ML courses), (2) *intermediate* level courses that cover major topics in *AIHD* and require advanced prerequisites, but with prerequisites structured in ways to make these courses accessible early on. Both of these approaches align with ways that make *AIHD* accessible.

Low *First Exposure* Level *AIHD* Courses

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

There were five AI courses with *first 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 ML but don't have the course schedule bandwidth to build up the math and computing background".

There were three ML courses with *first exposure* level 1 in our 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 putting the math prerequisites into a single course as a strategy for introducing ML earlier in the curriculum. In our US sample, there are 10 ML courses with *first 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 *AIHD* Courses

Although introductory *AIHD* courses can provide early exposure to key *AIHD* topics, access to advanced *AIHD* courses covering technical content rigorously is still important for undergraduate CS students. This section discusses how the *first exposure* level of such courses has been successfully reduced in Canadian and US institutions. Specifically, we focus on *AIHD* courses at the *intermediate* course level.Figure 4.4 and Figure 4.5 provide examples of such courses with lower exposure than usual.

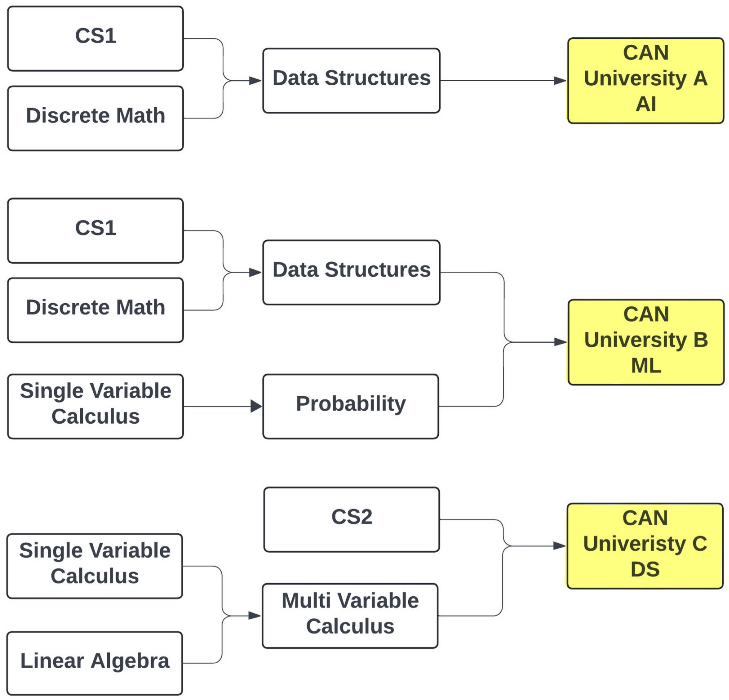


Figure 4.4: Prerequisites of intermediate *AIHD* courses in Canada (*AIHD* courses highlighted in yellow).

In Canada, there were 13 **AI courses** at the *intermediate* level, all of which had course titles similar to "Artificial Intelligence" or "Introduction to AI". One course had a *first exposure* level of 2, as indicated by the depth of the tree in Figure 4.4. This course requires 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 *first exposure* level 2, including the RL course. We selected the non-RL course to explore in Figure 4.4. The prerequisites required for this course follow Figure 4.2b: however, the prerequisite courses are 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 *first exposure* levels 2 and 4. The latter course had two *introductory* DS courses as prerequisites. We show the remaining course prerequisites in Figure 4.2b.

In US universities, there were 4 *intermediate* **AI courses**, with *first exposure* levels 0 to 3, all with similar titles as the Canadian counterparts. The minimum *first exposure* level courses either had no prerequisites or only a CS1 prerequisite, shown in Figure 4.5. There

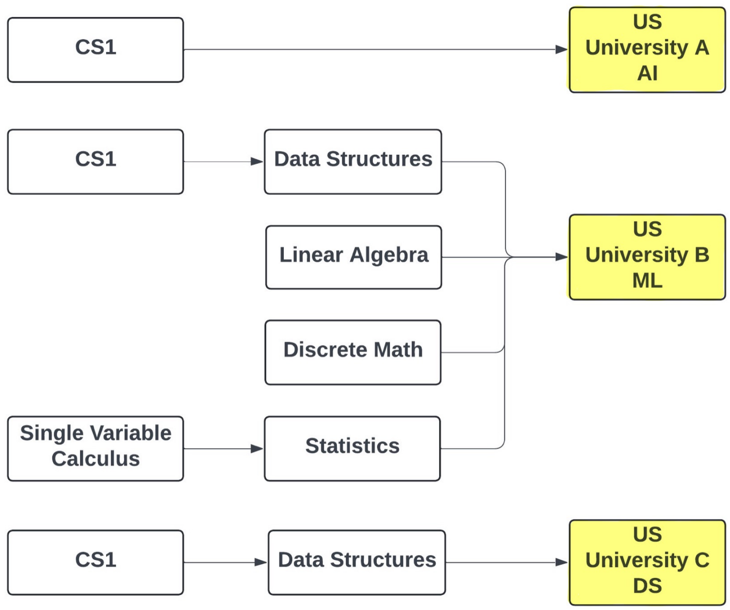


Figure 4.5: Prerequisites of intermediate *AIHD* courses in the US (*AIHD* courses highlighted in yellow).

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 *first exposure* level 2. Like the Canadian counterparts, the prerequisite structure of this course is highly parallelizable, allowing many prerequisite requirements but a low*first exposure* level. Finally, for intermediate **DS courses**, there were 6 in total, with a range of *first exposure* levels (2 courses with level 0, 1 with level 1, etc.). The course with *first exposure* level 1 required only CS1. The course with *first exposure* level 2 is shown in Figure 4.5.

Chapter 5

Discussion

5.1 Comparing Approaches of US and Canadian Institutions

First Exposure Levels

The differences in *first exposure* levels between US and Canadian *AIHD* courses, shown in Figure 4.1, highlight distinct curriculum priorities. It is worth noting that for Canadian universities, we did not restrict the sample to research-intensive institutions as we did for the US, so some differences may inherently reflect the priorities of the institution system. US institutions generally offer earlier access to *AIHD* topics, with AI and ML courses commonly available at *first exposure* level 2. In contrast, Canadian institutions delay these courses, requiring *first exposure* levels of 3 for AI and 4 for ML. This may reflect Canada's focus on ensuring a strong foundation in programming and math before tackling advanced topics. However, this delay might also limit opportunities for internships, research, and other hands-on experiences that require early AI and ML knowledge.

Both countries prioritize early engagement with DS concepts, but they take slightly different approaches. In the US, many DS courses are available at *first exposure* level 0, making them accessible to first-year students without prerequisites. Canadian institutions also offer some low *first exposure* level DS courses but balance this with higher-level DS courses. This dual approach may aim to introduce DS concepts early while allowing for advanced exploration later in the curriculum.

Prerequisite Chains

The prerequisite chains for *AIHD* courses differ greatly between US and Canadian institutions, as shown in Figure 4.2. US institutions streamline prerequisites by combining mathematical and theoretical foundations into broader courses like Discrete Mathematics or Data Structures. This reduces the total number of prerequisites, enabling students to reach AI and ML courses sooner. Canadian institutions, however, take a more segmented approach, requiring standalone courses like Mathematical Proofs and Advanced Programming before students can access advanced *AIHD* topics. While this approach ensures a solid foundation, it can create bottlenecks that slow progression.

Programming prerequisites also differ. US institutions often introduce OOP early, emphasizing practical skills. In Canada, OOP is typically offered after foundational courses like CS1 and CS2, ensuring a step-by-step progression. This sequencing approach can build strong fundamentals but also delay students from applying programming skills in interdisciplinary or applied *AIHD* contexts.

DS courses further highlight these differences. Canadian institutions often have uniform prerequisites, such as Statistics, for DS courses. In contrast, US institutions show more variety, requiring courses like Data Structures, CS2, or Data Management, depending on the course's goals. Similarly, Canadian ML courses often require prior AI coursework, creating a sequential path through the curriculum. In the US, ML courses frequently follow directly from math courses like Linear Algebra, bypassing AI as a prerequisite. These differences reflect Canada's layered progression and the US's more flexible pathways.

Clustering of Courses

The clustering analysis (Figure 4.3) highlights key similarities and differences in AI and ML course structures between Canada and the US.

Both countries emphasize foundational prerequisites like CS2, Data Structures, Linear Algebra, and Probability for advanced AI and ML courses, ensuring students are well-prepared for technical rigor. This consistency emphasizes the importance of strong computing and mathematical foundations. However, the US adopts a broader preparation strategy for ML courses, requiring diverse prerequisites such as Algorithms and Calculus. In contrast, Canadian ML courses focus on fewer but more specific prerequisites, like prior ML experience, streamlining the pathway for potentially limiting accessibility for newcomers. Introductory DS courses are highly accessible in both countries, typically requiring minimal prerequisites. This accessibility supports early engagement with computational concepts and encourages broader participation in DS education.

5.2 Strategies for Enhancing Accessibility and Early Exposure to *AIHD* Courses

Based on the results of RQ1 and RQ2, DS courses are generally more accessible compared to AI and ML courses. This accessibility stems from DS courses often having minimal or no prerequisites, making them available to students early in their academic journey. Leveraging this accessibility, one effective strategy is to incorporate basic AI and ML content into DS courses. By introducing foundational *AIHD* concepts within the context of DS, students can gain early exposure without the need for additional prerequisite-heavy courses. This approach provides a pathway for engaging students with AI and ML while building on the accessibility of DS education.

Our analysis from RQ3 shows that *AIHD* courses in Canada generally have higher *first exposure* levels than in the US, meaning Canadian students start engaging with these courses later in their academic careers. This delay reduces the time available for advanced study, participation in research, and internships that require the skills developed in these courses. Early exposure to *AIHD* topics is essential for enabling students to explore and specialize in these fields, which are increasingly in demand across industries. Canadian institutions could address this by revising course structures to introduce *AIHD* content earlier, aligning with practices observed in some US institutions where lower *first exposure* is more common. For example, courses with lower *first exposure* levels can act as an entry point, equipping students with foundational knowledge while maintaining accessibility.

In RQ3, we found that institutions in the US and Canada both adopted innovative approaches to enable students to engage with *AIHD* courses earlier. One effective approach is to offer introductory *AIHD* courses with little to no prerequisites. These courses could focus on interdisciplinary topics such as the history and philosophy of *AIHD* or provide a hands-on introduction to applied AI. Such courses not only lower the barriers to entry but also provide a broader context for understanding *AIHD*, sparking students' interest at an earlier stage of their education. Furthermore, offering these courses in the first year could help students from diverse academic backgrounds engage with *AIHD* concepts without feeling overwhelmed by technical prerequisites.

Another approach involves teaching prerequisites alongside some of the *AIHD* content, as suggested by Li and Liu [36]. For instance, courses could integrate foundational mathematics and programming concepts with introductory AI or ML topics, allowing students to gain exposure to advanced fields while simultaneously fulfilling their prerequisite requirements. This approach not only reduces the time required to progress through prerequisite chains but also fosters an immediate connection between theoretical knowledge and its practical applications.

In the second part of RQ4, our analysis of low *first exposure* level AI and ML courses revealed that parallelizing prerequisites is another effective strategy for enabling earlier entry into these fields. Successful examples demonstrate how parallelizing necessary computing and mathematics prerequisites, such as Linear Algebra and CS2, allows students to take these courses simultaneously rather than sequentially. This reduces the delay in entering AI and ML courses, enabling students to engage with advanced topics earlier in their academic careers. Early access to these courses can enhance students' ability to explore specialization areas, participate in research, and secure internships, ultimately preparing them for advanced study or industry roles.

However, early exposure strategies often require careful academic planning, especially for first-year students who may lack the knowledge or resources to structure their course pathways. Academic advising plays a critical role in guiding students through their learning pathways, ensuring they complete prerequisites efficiently and take advantage of opportunities for early engagement with *AIHD* courses. Advisors can help students optimize their schedules, avoid unnecessary delays, and ensure they are adequately prepared for advanced coursework. By combining academic advising with strategies like parallelizing prerequisites and integrating foundational content into early courses, institutions can greatly reduce entry barriers and broaden access to AI and ML courses.

5.3 Limitation and Future Work

Our data relies on publicly accessible course calendar information on the institutions' websites. However, this data may be incomplete or contain outdated information. The dynamic nature of course offerings in rapidly evolving fields such as *AIHD* means that some relevant courses might have been overlooked in their latest iteration. Future work could involve periodically updating the dataset with the latest information from institutional websites and incorporating surveys or interviews with faculty members to validate and supplement publicly available data.

As for data collection, there was an uneven geographical distribution of the sampled universities. The concentration of institutions within certain regions may influence the generalizability of our findings. To address this limitation, future studies could aim for a more geographically diverse sample, including universities from underrepresented regions. In addition, this could involve partnerships with international organizations or networks that focus on AI education, enabling a more global understanding of curriculum design.

Moreover, we only considered courses offered by CS departments, which may have excluded courses from other departments that also contributed to education in *AIHD*Ṫhese departments can include mathematics, statistics, engineering, or even the social sciences, where interdisciplinary *AIHD* courses are offered. Failing to account for such courses means that the data may not fully capture the breadth of AI education provided across institutions. Future research could expand the scope to include interdisciplinary courses. This would provide a broader view of how AI education is integrated across various fields and highlight potential collaborations between departments that could enrich *AIHD* curricula.

Another potential limitation is the lack of student-specific data, such as enrollment demographics, prior preparation, or post-course outcomes. This omission makes it difficult to assess the effectiveness of different curricular structures in terms of student success, retention, or career readiness. Future research could integrate student data to analyze how variations in curriculum design impact diverse student populations.

Finally, we did not analyze the *first exposure* level of the courses relative to the course level (e.g. Introductory, Intermediate, etc.). Some low *first exposure* AI or ML courses could be advanced-level courses without explicit prerequisites listed on the website, potentially assuming a prior knowledge of mathematics, programming, or other foundational topics. Future work could involve validating course levels and prerequisite assumptions through direct communication with course instructors. This would provide a more accurate picture of whether low *first exposure* courses truly represent accessible entry points for students.

Chapter 6

Conclusion

In conclusion, this report examines the structures of AI curricula in North America, focusing on the accessibility and timing of *AIHD* course exposure for undergraduate students. The analysis reveals similarities and differences in how prerequisites are structured and how early students can engage with *AIHD* courses within the US and Canada. US institutions generally offer earlier exposure and more flexible pathways compared to their Canadian counterparts. The findings highlight the importance of reducing entry barriers through strategies such as parallelizing prerequisites, integrating foundational content into introductory courses, and offering accessible interdisciplinary *AIHD* courses. These approaches not only broaden access to AI education but also prepare students earlier for advanced study, research, and industry opportunities. By proposing a comprehensive codebook, an exposure-level metric, and a comparative framework, this work provides actionable recommendations for designing inclusive and accessible AI curricula, ultimately contributing to the preparation of a diverse and capable AI workforce. Future research should expand to include interdisciplinary perspectives, integrate student-level data, and evaluate the long-term impacts of curriculum structures on educational outcomes.

Bibliography

[1] Lorena Espina-Romero et al. “Which industrial sectors are affected by artificial intelligence? A bibliometric analysis of trends and Perspectives”. In: *Sustainability* 15.16 (2023), p. 12176.

[2] Sandeep Reddy et al. “A governance model for the application of AI in health care”. In: *Journal of the American Medical Informatics Association* 27.3 (2020), pp. 491–497.

[3] Longbing Cao. “Ai in finance: challenges, techniques, and opportunities”. In: *ACM Computing Surveys (CSUR)* 55.3 (2022), pp. 1–38.

[4] Kanna Rajan and Alessandro Saffiotti. *Towards a science of integrated AI and Robotics*. 2017.

[5] Eric Horvitz. *AI, people, and society*. 2017.

[6] Paul Denny et al. “Generative AI for Education (GAIED): Advances, Opportunities, and Challenges”. In: *arXiv preprint arXiv:2402.01580* (2024).

[7] Ainhoa Urtasun Alonso. “Empowering undergraduates through machine learning”. In: *Industry and Higher Education, 36 (3), 443-447* (2022).

[8] Pat Langley. “An integrative framework for artificial intelligence education”. In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 33. 01. 2019, pp. 9670–9677.

[9] Iain M Cockburn, Rebecca Henderson, and Scott Stern. “The impact of artificial intelligence on innovation: An exploratory analysis”. In: *The economics of artificial intelligence: An agenda*. University of Chicago Press, 2018, pp. 115–146.

[10] Jianing Xia, Man Li, and Jianxin Li. *Comparative Analysis Vision of Worldwide AI Courses*. 2024. arXiv: `2407.16881 [cs.CY]`. URL: `https://arxiv.org/abs/2407.16881`.

[11] Agostinho Sousa Pinto et al. “How machine learning (ml) is transforming higher education: A systematic literature review”. In: *Journal of Information Systems Engineering and Management* 8.2 (2023).

[12] Daphne Barretto et al. "Exploring Why Underrepresented Students Are Less Likely to Study Machine Learning and Artificial Intelligence". In: *Proceedings of the 26th ACM Conference on Innovation and Technology in Computer Science Education V. 1*. 2021, pp. 457–463.

[13] Shannon Wongvibulsin. "Educational strategies to foster diversity and inclusion in machine intelligence". In: *Nature machine intelligence* 1.2 (2019), pp. 70–71.

[14] Orit Hazzan and Koby Mike. "The Pedagogical Challenge of Machine Learning Education". In: *Guide to Teaching Data Science: An Interdisciplinary Approach*. Springer, 2023, pp. 199–208.

[15] Becky Allen, Andrew Stephen McGough, and Marie Devlin. "Toward a framework for teaching artificial intelligence to a higher education audience". In: *ACM Transactions on Computing Education (TOCE)* 22.2 (2021), pp. 1–29.

[16] Lisa Zhang and Sonya Allin. "Just-In-Time Prerequisite Review for a Machine Learning Course". In: *Proceedings of the 25th Western Canadian Conference on Computing Education*. 2023, pp. 1–2.

[17] Maithilee Kunda. "The AI Triplet: Computational, Conceptual, and Mathematical Knowledge in AI Education". In: *arXiv preprint arXiv:2110.09290* (2021).

[18] Marion Neumann. "AI education matters: a first introduction to modeling and learning using the data science workflow". In: *AI Matters* 5.3 (2019), pp. 21–24.

[19] Johanna S Hardin and Nicholas J Horton. "Ensuring that mathematics is relevant in a world of data science". In: *Notices of the AMS* 64.9 (2017), pp. 986–990.

[20] Adrian A de Freitas and Troy B Weingart. "I'm going to learn what?!? teaching artificial intelligence to freshmen in an introductory computer science course". In: *Proceedings of the 52nd ACM technical symposium on computer science education*. 2021, pp. 198–204.

[21] André Renz and Romy Hilbig. "Prerequisites for artificial intelligence in further education: Identification of drivers, barriers, and business models of educational technology companies". In: *International Journal of Educational Technology in Higher Education* 17.1 (2020), p. 14.

[22] Thomas KF Chiu et al. "Creation and evaluation of a pretertiary artificial intelligence (AI) curriculum". In: *IEEE Transactions on Education* 65.1 (2021), pp. 30–39.

[23] David Touretzky et al. "Envisioning AI for K-12: What should every child know about AI?" In: *Proceedings of the AAAI conference on artificial intelligence*. Vol. 33. 01. 2019, pp. 9795–9799.

[24] Amruth N. Kumar et al. *Computer Science Curricula 2023*. New York, NY, USA: Association for Computing Machinery, 2024. ISBN: 9798400710339.

[25] Mark Guzdial and Benedict du Boulay. "The history of computing". In: *The Cambridge handbook of computing education research* 11 (2019).

[26] Mordechai Ben-Ari. "Constructivism in computer science education". In: *Acm sigcse bulletin* 30.1 (1998), pp. 257–261.

[27] Stephen H Edwards. "Using software testing to move students from trial-and-error to reflection-in-action". In: *Proceedings of the 35th SIGCSE technical symposium on Computer science education*. 2004, pp. 26–30.

[28] Henry M. Walker. "Prerequisites: shaping the computing curriculum". In: *ACM Inroads* 1.4 (Dec. 2010), pp. 14–16. ISSN: 2153-2184. DOI: `10.1145/1869746.1869751`. URL: `https://doi.org/10.1145/1869746.1869751`.

[29] S. Thomas and R. Lightfoot. "EXPLORING THE IMPACT OF PREREQUISITES AND ELECTIVE CHOICE ON DOWNSTREAM UPPER-LEVEL COMPUTER SCIENCE COURSES". In: *ICERI2024 Proceedings*. 17th annual International Conference of Education, Research and Innovation. Seville, Spain: IATED, Nov. 2024, pp. 7062–7068. ISBN: 978-84-09-63010-3. DOI: `10.21125/iceri.2024.1698`. URL: `https://doi.org/10.21125/iceri.2024.1698`.

[30] Sander Valstar, William G Griswold, and Leo Porter. "The relationship between prerequisite proficiency and student performance in an upper-division computing course". In: *Proceedings of the 50th ACM Technical Symposium on Computer Science Education*. 2019, pp. 794–800.

[31] Sophia Krause-Levy et al. "Instructor Perspectives on Prerequisite Courses in Computing". In: *Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 1*. 2023, pp. 277–283.

[32] Udayan Das and Chris Fulton. "Reducing Barriers to Entry by Removing Prerequisites for a CS1 Introductory Programming Course". In: *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 2*. SIGCSE 2024. Portland, OR, USA: Association for Computing Machinery, 2024, pp. 1616–1617. ISBN: 9798400704246. DOI: `10.1145/3626253.3635492`. URL: `https://doi.org/10.1145/3626253.3635492`.

[33] Udayan Das and Chris Fulton. "Reducing Barriers to Entry by Removing Prerequisites for a CS1 Introductory Programming Course". In: *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 2*. 2024, pp. 1616–1617.

[34] Carla E. Brodley, McKenna Quam, and Mark A. Weiss. *An Analysis of the Math Requirements of 199 CS BS/BA Degrees at 158 U.S. Universities*. 2024. arXiv: `2404.15177 [cs.CY]`. URL: `https://arxiv.org/abs/2404.15177`.

[35] Yang Song. "Redesigning a Computer Science Capstone Course with Micro-credentials". In: *2018 IEEE Frontiers in Education Conference (FIE)*. IEEE. 2018, pp. 1–5.

[36] Miaomiao Li and Bo Liu. "A Brief Discussion on the Reform of Mathematics Teaching in Artificial Intelligence Majors-Taking Matrix Computation and Optimization as Examples". In: *National Conference of Theoretical Computer Science*. Springer. 2022, pp. 132–141.

[37] Lisha Hu and Chunyu Hu. "Fusion of Machine Learning for Teaching Case Research on Algorithm Course". In: *2021 11th International Conference on Information Technology in Medicine and Education (ITME)*. IEEE. 2021, pp. 569–572.

[38] Chinmay Sahu, Blaine Ayotte, and Mahesh K Banavar. "Integrating machine learning concepts into undergraduate classes". In: *2021 IEEE Frontiers in Education Conference (FIE)*. IEEE. 2021, pp. 1–5.

[39] Vandana P Janeja et al. "Adopting Foundational Data Science Curriculum with Diverse Institutional Contexts". In: *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*. 2024, pp. 576–582.

[40] R Benjamin Shapiro, Rebecca Fiebrink, and Peter Norvig. "How machine learning impacts the undergraduate computing curriculum". In: *Communications of the ACM* 61.11 (2018), pp. 27–29.

[41] Davy Tsz Kit Ng et al. "A review of AI teaching and learning from 2000 to 2020". In: *Education and Information Technologies* 28.7 (2023), pp. 8445–8501.

[42] Becky Allen, Andrew Stephen McGough, and Marie Devlin. "Toward a Framework for Teaching Artificial Intelligence to a Higher Education Audience". In: *ACM Trans. Comput. Educ.* 22.2 (Nov. 2021). DOI: 10.1145/3485062. URL: https://doi.org/10.1145/3485062.

[43] Yong Zheng. "A Course on Applied AI and Data Science: Recommender Systems". In: SIGITE '19. Tacoma, WA, USA: Association for Computing Machinery, 2019, pp. 43–48. ISBN: 9781450369213. DOI: 10.1145/3349266.3351405. URL: https://doi.org/10.1145/3349266.3351405.

[44] Koby Mike, Tamir Hazan, and Orit Hazzan. "Equalizing data science curriculum for computer science pupils". In: *Proceedings of the 20th Koli Calling International Conference on Computing Education Research*. 2020, pp. 1–5.

[45] Aimee Schwab-McCoy, Catherine M Baker, and Rebecca E Gasper. "Data science in 2020: Computing, curricula, and challenges for the next 10 years". In: *Journal of Statistics and Data Science Education* 29.sup1 (2021), S40–S50.

[46] Alpay Sabuncuoglu. "Designing one year curriculum to teach artificial intelligence for middle school". In: *Proceedings of the 2020 ACM conference on innovation and technology in computer science education*. 2020, pp. 96–102.

[47] Weipeng Yang. "Artificial Intelligence education for young children: Why, what, and how in curriculum design and implementation". In: *Computers and Education: Artificial Intelligence* 3 (2022), p. 100061.

[48] Ismaila Temitayo Sanusi et al. "A systematic review of teaching and learning machine learning in K-12 education". In: *Education and Information Technologies* 28.5 (2023), pp. 5967–5997.

[49] Jiahong Su and Yuchun Zhong. "Artificial Intelligence (AI) in early childhood education: Curriculum design and future directions". In: *Computers and Education: Artificial Intelligence* 3 (2022), p. 100072.

[50] *AI for K-12*. `https://ai4k12.org/`. Accessed: 2024-12-19. 2024.

[51] Andrej Thurzo et al. "Impact of artificial intelligence on dental education: A review and guide for curriculum update". In: *Education Sciences* 13.2 (2023), p. 150.

[52] Elena A Wood, Brittany L Ange, and D Douglas Miller. "Are we ready to integrate artificial intelligence literacy into medical school curriculum: students and faculty survey". In: *Journal of medical education and curricular development* 8 (2021), p. 23821205211024078.

[53] Jennifer J Xu and Tamara Babaian. "Artificial intelligence in business curriculum: The pedagogy and learning outcomes". In: *The International Journal of Management Education* 19.3 (2021), p. 100550.

[54] Narges Norouzi, Snigdha Chaturvedi, and Matthew Rutledge. "Lessons learned from teaching machine learning and natural language processing to high school students". In: *Proceedings of the AAAI conference on artificial intelligence*. Vol. 34. 09. 2020, pp. 13397–13403.

[55] Helen Crompton and Diane Burke. "Artificial intelligence in higher education: the state of the field". In: *International Journal of Educational Technology in Higher Education* 20.1 (2023), p. 22.

[56] Prajukti Bhattacharyya and Catherine WM Chan. "Can undergraduate research participation reduce the equity gap?" In: *Journal of the Scholarship of Teaching and Learning* 21.1 (2021).

[57] Christine Alvarado, Sergio Villazon, and Burcin Tamer. "Evaluating a scalable program for undergraduate CS research". In: *Proceedings of the 2019 ACM Conference on International Computing Education Research*. 2019, pp. 269–277.

[58] Jennifer S Stanford et al. "Early undergraduate research experiences lead to similar learning gains for STEM and Non-STEM undergraduates". In: *Studies in Higher Education* 42.1 (2017), pp. 115–129.

[59] Marcia C Linn et al. "Undergraduate research experiences: Impacts and opportunities". In: *Science* 347.6222 (2015), p. 1261757.

[60] Olivier Bégin-Caouette et al. "Canada: The role of the university sector in national research and development". In: *Universities in the knowledge society: The Nexus of National Systems of Innovation and Higher Education* (2021), pp. 375–392.

[61] Mohammad Mehdi Ebadi et al. "Comparison of the civil engineering curriculum among several Canadian universities". In: *Proceedings of the Canadian Engineering Education Association (CEEA)* (2020).

[62] Aidan Pucchio et al. "Exploration of exposure to artificial intelligence in undergraduate medical education: a Canadian cross-sectional mixed-methods study". In: *BMC medical education* 22.1 (2022), p. 815.

[63] Mary L McHugh. "Interrater reliability: the kappa statistic". In: *Biochemia medica* 22.3 (2012), pp. 276–282.