Mapping the Pathways: A Comparative Analysis of AI/ML/DS Prerequisite Structures in R1 Institutions in the United States

***Abstract*—This Research Full paper focuses on the challenges in artificial intelligence, machine learning, and data science education, which often deal with extensive prerequisites limiting student access. Early access to coursework in these areas is critical to enabling earlier undergraduate research engagement and, hence, enhancing academic retention. We analyze the course structures and prerequisites of artificial intelligence, machine learning, and data science courses, referred to as "artificial intelligence" courses here on, offered in computing departments of 50 Research-1 institutions in the United States and conduct a systematic review. Our analysis specifically targets Research-1 institutions, recognized for their "Very High Research Activity," to investigate the process and the associated timeline that prepares students for research in artificial intelligence during their undergraduate educational journey.**

Specifically, we are interested in students' earliest exposure to these courses and institutions' common and different approaches to structuring prerequisites. Thus, we analyze course syllabi from 50 Research-1 universities, focusing on the structure and prerequisites of artificial intelligence courses. We categorized courses based on their course descriptions while collecting additional information, such as the frequency of offerings and course level (first-year, second-year, etc.). To systematically analyze the prerequisites, we employed open coding to develop a unified codebook to identify immediate prerequisites. We use the prerequisite information to build a prerequisite chain to determine the earliest exposure levels for these courses. Finally, we conducted a clustering analysis on courses and institutions to understand common and differing approaches in curriculum design.

Results reveal that public Research-1 institutions offer advanced courses with greater exposure and fewer prerequisites than private institutions, both of which provide easily accessible introductory courses. Data science requires less initial exposure, while machine learning requires more prerequisites. Standard requirements for the artificial intelligence course include algorithmic foundations and CS1, with the machine learning course requiring more mathematics preparation.

Overall, this study recognizes the considerable diversity in the curricular frameworks in Research-1 institutions, offering a detailed perspective on the complexities and potential pathways for standardizing education in artificial intelligence. This study encourages institutions to revise their curricula to broaden educational access to artificial intelligence, aiming to increase undergraduate participation in artificial intelligence research.

***Index Terms*—Article submission, IEEE, IEEEtran, journal, LaTeX, paper, template, typesetting.**

I. Introduction

There has been increased interest in areas related to Artificial Intelligence (AI), Machine Learning (ML), and Data Science (DS), (referred to as *AI* courses here on) as well as applications of these areas in various fields [1]–[4]. Integrating such disciplines in the educational framework is highly demanded in any industry today [5] as it prepares students to drive innovation and address complex challenges in a variety of sectors [6], [7]. However, *AI* fields face challenges in ensuring diversity [8], [9]. Studying and teaching *AI* have been reported by both students and instructors as challenging [6], [10], [11] and Computer Science (CS) educators often hesitate to teach *AI* subjects to non-major students due to their complexity [12]. Learning these topics often requires a grasp of a range of mathematical prerequisite skills like calculus, linear algebra, and probability, as well as programming skills [13]–[16]. Such requirements can potentially delay students from engaging in these fields at early stages.

Our study analyzes R1 (Research-1): Doctoral Universities in the United States (U.S.) with "Very High Research Activity" from the Carnegie classification[1]. We specifically focus on R1 institution since we want to investigate the process and the associated timeline that prepares students for AI research after taking relevant courses. Our study aims to compare and contrast the various curriculum designs across institutions to evaluate student accessibility to *AI* courses and understand the effects of a light prerequisite structure on students' readiness for AI research.

We seek to answer the following three research questions:

- **RQ1**. What is the earliest exposure of students to the *AI* curriculum?
- **RQ2**. What common approaches are institutions using to structure prerequisites for *AI* courses in R1 computing departments in the U.S.?
- **RQ3**. What different approaches are institutions using to structure prerequisites for *AI* courses in R1 computing departments in the U.S.?

This study intends to guide educational institutions in creating learning pathways that are rigorous yet flexible and align with the evolving demands of *AI* to balance the need for foundational knowledge with accessible research entry points into these fields.

II. Related Work

Previous studies showed the importance and impact of *AI* courses on a diverse group of students. Ng et al. [17] emphasized the importance of AI in education, noting a shift from traditional university-level CS to inclusive methods for K-12 and non-technical learners. In addition, AI education can be taught to non-technical majors as well. Menkhoff and Lydia Teo [18] conducted a case study with its chatbot

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

workshop to non-technical undergraduate students to teach basic skills in the freshman AI course. Moreover, de Freitas and Weingart [12] demonstrated that AI concepts can be effectively taught to non-technical students with a curriculum specifically designed for first-year students. These findings confirm the versatility and applicability of AI education across diverse technical levels of students.

The CS community is interested in examining the role of prerequisites in education. Krause-Levy et al . [19] examined instructors' views on computing education prerequisites, revealing the complexity of prerequisite course implementation and the challenges instructors face when aligning course content with student preparation and curriculum requirements. Another study by Krause-Levy et al. [20] analyzed demographic factors affecting students' readiness for an Advanced DS course. The study revealed disparities in prerequisite proficiency among different student groups and emphasized the importance of addressing diverse educational backgrounds in the field. Krause-Levy et al. [21] found significant correlations between students' success in prerequisite courses and their performance in the advanced course, suggesting that performance in prerequisites strongly predicts success in subsequent advanced computing courses.

There are diverse approaches in which prerequisites are integrated into *AI* courses. Li and Liu [22] emphasize the importance of core theoretical courses like "Matrix Computation" and "Optimization" as prerequisites in AI. Another study found that incorporating just-in-time prerequisite reviews, consisting of targeted questions and instructional videos before each lecture, effectively addressed knowledge gaps in ML courses [13].

Previous studies demonstrate that *AI* can be taught even without extensive technical prerequisites. Barretto et al. [8] 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. Moreover, in a month-long course teaching ML and Natural Language Processing (NLP) to high school students who were taught coding in the course itself, students enhanced their understanding of AI and underscored the importance of foundational programming skills in AI education [23]. Allen et al . [11] advocates for a combination of 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.

With all the recent advancements, interest in conducting AI research has risen dramatically, particularly with undergraduates [24]. However, oftentimes, AI research is not available to students without related experience in coursework. Access to AI courses at an early stage empowers students to engage in undergraduate research earlier. This has important implications for student retention, as Bhattacharyya et al . [25] found that engaging in undergraduate research increased student retention rate and graduation rates.

The previous studies primarily focused on demographic analyses, instructor perspectives, and the relationship between prerequisite courses and student performance in specific computing courses. Our research is unique in that it systematically reviews the curriculum approaches of *AI* courses across R1 institutions, analyzing how prerequisites influence course accessibility and AI research preparation eventually.

III. Methodology

A. Data Collection

We randomly sampled 50 R1 universities. Our sample included 37 public universities and 13 private universities. To be included in our sample, the institution must have a computing department advertised on their institution's website. Institutions must also have at least one AI, ML, or DS course offered by their computing department. We excluded and resampled two universities that were originally in our sample but did not have a computing department and did not have any undergraduate courses offered. The geographic distribution of the sampled universities across the U.S. is illustrated in Figure 1.

We then collected, for each institution, the list of undergraduate *AI* courses offered by their computing department. To define *AI* courses, we first identified relevant courses from each institution's academic calendar. The criteria for classifying a course as AI, ML, or DS were based on the 2023 offering guidelines, examining the course syllabi. This process helped ensure that the courses selected were representative of the respective subjects. We considered whether any edge cases emerged in this categorization, but such instances were not prevalent. In terms of inclusion and exclusion, we ruled out special topic courses and those that were not recently offered, to maintain relevancy and accuracy. For each relevant undergraduate course, we collected the course type (AI, ML, or DS), course name, level, immediate course prerequisites, and offering frequency. "Introductory", "Intermediate", "Advanced", and "Cross-listed" (courses open to both undergraduate and graduate students), based on each university's course

TABLE I
Breakdown of University Type

University Type	Number
Public	37
Private	13

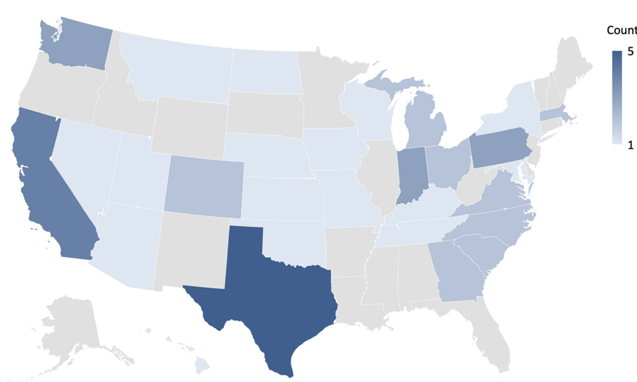

Fig. 1. Sampled university distribution across the U.S.

TABLE II
DISTRIBUTION OF COURSE LEVELS FOR AI, ML, AND DS.

Course Type	Number of Courses	Average Course Level	Min Course Level	Max Course Level	Mode Course Level	Mode Frequency
AI	55	2.96	1	4	3	Once a year
ML	54	3.02	2	4	3	Once a year
DS	40	2.33	1	4	3	More than once a year

numbering scheme. The offering frequency was categorized into "More than once a year", "Once a year", and "Less than once a year", aligning with the universities' academic schedules. The definitions of "Introductory", "Intermediate", and "Advanced" were established based on course content complexity and prerequisite requirements, as outlined in the respective university catalogs.

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

Further, as shown in Table II, 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. Both AI and DS had a minimum course level of introductory, whereas ML had a minimum course level of intermediate. All three subjects were most often offered at the advanced level. Further, AI and ML courses were most often offered once a year, whereas DS courses were most often offered more than once a year.

B. Coding of Prerequisites

To give structure to the diverse set of prerequisites provided by each university, we first gathered information on the immediate prerequisites of each course. Three researchers, also authors of this study, independently conducted open coding of each course, resulting in three sets of codes. Next, the three sets were merged into a single codebook. During this phase, 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 III.

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. During this part, any discrepancies were discussed, and additional modifications were made to the coding, particularly in instances where courses spanned multiple topics. This iterative process resulted in achieving a high level of inter-rater reliability, as evidenced by a Cohen's kappa score of 0.95, high substantial agreement [26].

C. First Exposure Level

To understand the earliest availability stage of *AI*courses (RQ1), we place a heavy emphasis on determining the earliest

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

TABLE III
CATEGORIZATION OF CODE NAMES.

Category	Code Names
Mathematics	Discrete Mathematics, Linear Algebra, Multi-variable Calculus, Probability, Statistics, Single-variable Calculus
Computing	Algorithmic Foundations, 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

entry point at which a student can engage with these courses. Thus, we analyzed how the first exposure levels and prerequisite chains differed between course types. We detailed the differences in the distribution of first exposure levels between *AI* courses by plotting a histogram for each course type.

D. Common Prerequisite Approach

To understand the common prerequisite approaches (RQ2), we developed a Sankey graph plotting each course's prerequisite chain. We chose this graph to visualize which prerequisites were the most foundational for each of the *AI* courses, as well as which prerequisites were most often required. To that end, for each of the 50 institutions in our sample, we construct a prerequisite graph: a directed graph where the nodes are courses needed to take one of the *AI* courses, and the edges denote direct prerequisite relation. This approach allowed us to trace back each course to its direct and indirect prerequisites and can thus help determine *the first exposure level*: the depth of each course within the prerequisite hierarchy. For example, a course with several layers of prerequisites would indicate a higher first exposure level compared to a course that is directly connected to the initial course.

E. Clustering Analysis

To reveal the characteristics of different institutions and their corresponding courses (RQ3), we use a clustering method. Specifically, we analyzed the data using k-means clustering to create clusters at the course and institution levels. Our features for the course level analysis were using five categories: Type of course, course level, course frequency, prerequisite statistics, and prerequisite courses using the aforementioned codebook. These groups of features were necessary to define how *AI* is

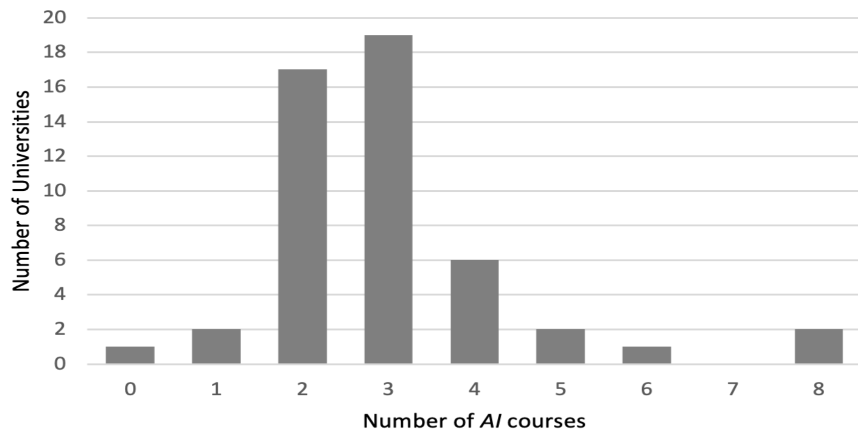

Fig. 2. Number of AI, ML, and DS courses per university.

currently being offered in R1 institutions because they capture statistics related to access to courses. By taking into account course levels and prerequisites, we could determine the first term where students may be able to enroll in *AI* courses. Further, the course frequency metric offered insights into barriers to access to classes even after prerequisites are completed. Through our analysis, we hope to expose the roadblocks students may face to access these courses, and therefore, potential roadblocks in their pursuit of research opportunities. Our university-level features included: course level, frequency, immediate prerequisite courses, total prerequisites, and first exposure level, as calculated by the averages over the relevant *AI* courses at the university.

For k-means clustering, we used one-hot encoding to represent categorical features. Our k-values were chosen based on the highest silhouette score between 2 and $\sqrt{n/2}$, a common heuristic to find an optimal k, where n is the number of data points. This resulted in 8 clusters for the course level and 4 clusters for the university level clustering.

IV. Results

A. Distribution of Exposure Level: RQ1

We compared the first exposure levels of different course types as shown in Figure 3. Observations from the figure suggest that DS courses tend to be more introductory, as indicated by lower exposure levels. In comparison, AI and ML courses show higher and more advanced exposure levels, with ML courses reaching the highest level of five, suggesting more advanced content than AI courses, which peak at four.

B. Relationship Between Prerequisites: RQ2

As shown in Figure 4, all prerequisite chains were based on one of three-course types: CS1 for more coding-related courses and Linear Algebra or Single-variable calculus for more mathematics-related courses. DS courses generally require minimal prerequisites, with only a handful of universities requiring various prerequisites like an Algorithmic Foundations course or a CS2 course. Meanwhile, AI courses generally require a strong programming background as seen by the prerequisite chains starting from CS1. ML courses require even more preparation, as they often possess long prerequisite chains on both the programming and mathematics sides, originating from CS1 and Single-variable Calculus, respectively.

C. Course Level Clustering: RQ3

To understand the different approaches that institutions use to structure *AI* prerequisites, we study the clustering of different courses offered by the sampled institutions. Figure 5 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 prevalent each feature was to the cluster. A lighter shade, such as yellow, indicates that including that feature was more prevalent in that cluster than it was in others. For example, the first cluster has a yellow color for AI, which means that its cluster is defined by having AI courses. A darker shade, such as navy blue, indicates that the lack of a feature helped define that cluster. Notably, the dark blue in Cluster 6 for the "Once a Year" feature indicates that the cluster mostly contains courses that were 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 it was to other clusters.

Using these definitions, we find that features including course type, course level, and some of the prerequisite features help define our clusters as seen by the light yellows and dark blues in those regions. However, features such as 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 8 clusters are each defined by the following features:

1) AI courses, advanced level, offered once a year, common prerequisites include Algorithmic Foundations and CS1 (N=45).
2) ML courses, advanced level, offered once a year, low number of immediate prerequisites, and common prerequisites include CS1 and CS2 (N=31).
3) ML Courses, advanced level, offered once a year, high level of total and immediate prerequisite courses, and

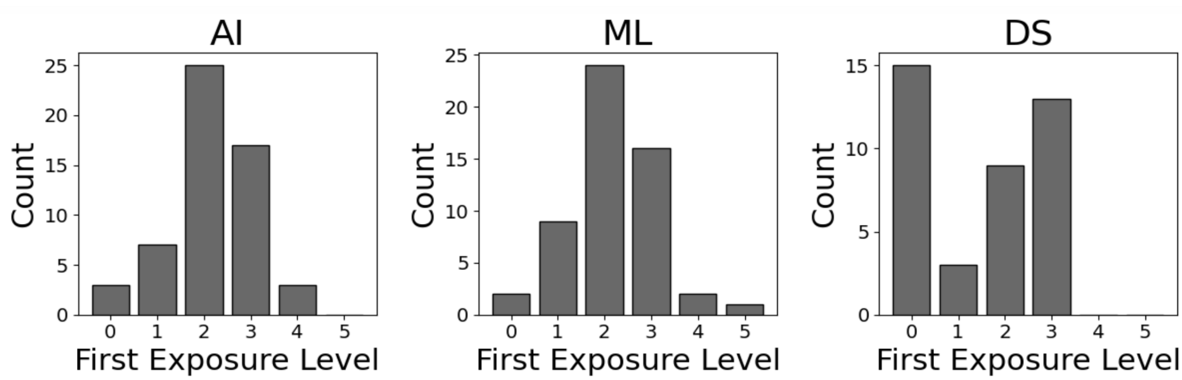

Fig. 3. Exposure levels of AI, ML, and DS courses.

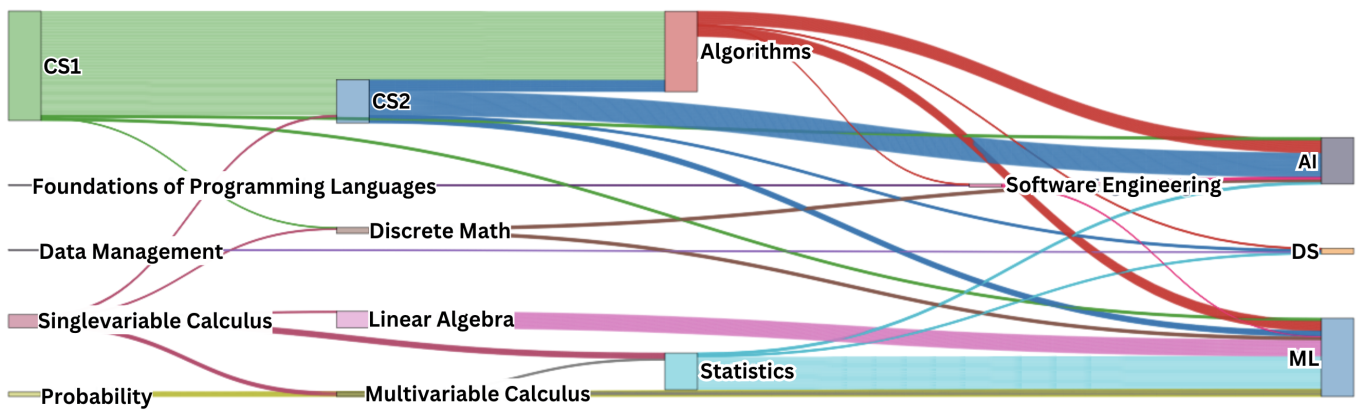

Fig. 4. Sankey diagram of prerequisite relationships. The nodes represent prerequisite courses, and the lines connecting each node represent the relationships. For example, if one university's AI course has their CS2 course as a prerequisite, which in turn has CS1 as a prerequisite, two lines would be 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 which occur less than 3 times are not plotted for graph clarity. Notably, DS courses have relatively few prerequisites as seen by its sparse and think connections.

common prerequisites include CS1, CS2, 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 Algorithmic Foundations, 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 Algorithmic Foundations, CS1, CS2, and Data Management (N=5).

D. University Level Clustering: RQ3

We also looked at the institution level, and the clusters were based on the following features: public vs. private institutions, course levels, exposure levels, prerequisite numbers, and frequency. The four centroids informed our clustering analysis. Figure 6 is a heatmap of the university clusters, with the same coloring scheme as the course clusters.

The clusters have the following characteristics:

1) Public institutions, advanced course levels, high first exposures (N=25).
2) Public institutions, frequently offered courses and lower number of prerequisites (N=11).
3) Private institutions, a high number of average prerequisites (N=10).
4) Public and private institutions, introductory course levels, infrequent offerings, minimal total prerequisites, low first exposure (N=4).

V. Discussion

RQ1. What is the earliest exposure of students to the *AI* curriculum?

Nearly a third of universities offer DS courses with no prerequisites, allowing students to engage with DS from their first term. This contrasts with AI and ML courses, typically requiring two to three semesters of prerequisites. The results suggest that DS is considered a fundamental subject in early heatmap-courses.png

Fig. 5. Heatmap of course clusters. Each column represents a feature (course type, level, frequency, number of prerequisites, prerequisite courses).

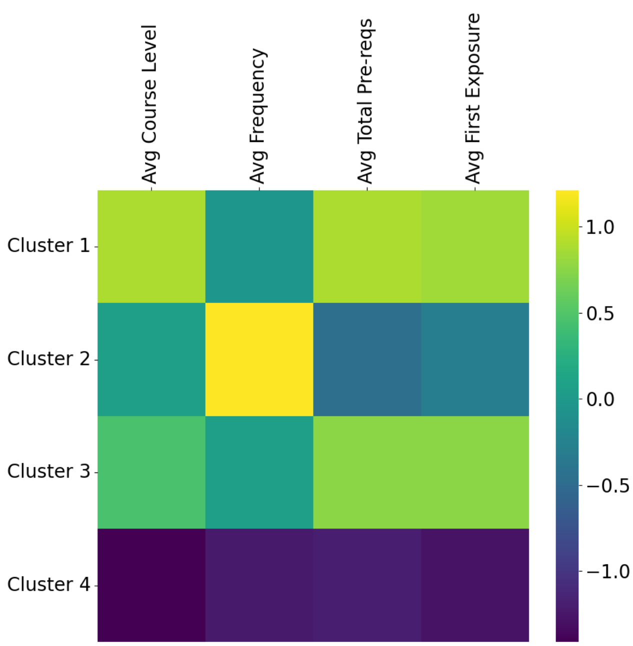

Fig. 6. Heatmap of university clusters.

university education. While AI and ML are positioned as advanced subjects, accessible after building a foundational knowledge base in the first year.

RQ2. What common approaches are institutions using to structure prerequisites for *AI* courses in R1 computing departments in the U.S.?

AI courses typically require a strong programming background, often starting with CS1 courses as prerequisites. This indicates a focus on coding skills as essential for AI courses. ML courses, on the other hand, demand extensive preparation in both programming and mathematics. Their long prerequisite chains usually begin with CS1 and Single-variable Calculus, reflecting the need for a deeper understanding of both fields. Compared to AI and ML, DS courses are more accessible, generally requiring fewer prerequisites and thus positioned as a more introductory subject in the curriculum. However, Figure 4 shows that a keen student should be able to satisfy the prerequisites to take an ML course in the latter half of year 2 of study if the university's curriculum allows it.

RQ3. What different approaches are institutions using to structure prerequisites for *AI* courses in R1 computing departments in the U.S.?

Introductory AI courses typically require fewer prerequisites compared to ML courses, indicating easier access for beginners. Some ML courses require DS as a prerequisite, suggesting an institutional focus on integrating DS skills in ML education. Private universities offer these courses more frequently and with fewer prerequisites than public universities, facilitating quicker access to AI and ML studies. In contrast, public universities have higher-level introductory courses, potentially providing a more thorough foundational education in these fields, but with delayed student exposure.

Overall, the findings suggest that there is a range of approaches to *AI* curricula. Many institutions offer introductory DS courses showing that such courses are providing students with early exposure to AI-related content. Structuring AI and ML courses to gradually build on the foundational knowledge provided by early DS courses can be another strategy to structure a progressive learning journey for students in these fields.

VI. Limitations

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 *AI* means that some relevant courses might have been overlooked in their latest iteration. Prerequisite links were also collected from the publicly accessible academic calendar, and may not capture prerequisite and course requirements that are not explicitly listed.

Moreover, we only considered courses offered by the computing department, which may exclude courses from other departments that also contribute to education in *AI*.

VII. Future Work

In future work, we plan to explore the impact of initial course entry points on students' subsequent engagement in AI research. Given R1 institutions' heavy emphasis on research, this investigation will involve a longitudinal study that tracks students from their exposure to *AI* courses to their active participation in AI research. We will focus on analyzing the timing of research engagement relative to coursework and retention rates within the AI field. We are interested in determining how early exposure to *AI* courses influences students' involvement and success in research activities, thereby providing insights into optimizing educational pathways in AI.

Further investigation is also suggested into whether certain prerequisite structures act as barriers to entry, This exploration could involve examining the impact of different prerequisite configurations on student accessibility and success.

In addition, incorporating qualitative data supplement to our current analysis through collaboration with professors and industry professionals is another direction for future research to make *AI* accessible at an earlier exposure. This collaboration would involve a qualitative analysis such as interviews to determine the most effective course structures for achieving various goals, such as conducting research in specific areas. Such insights can provide a more nuanced understanding of how educational frameworks can be tailored to meet diverse career and research objectives [27], [28].

VIII. Conclusion

Our study showed variations in course accessibility in R1 institutions in the U.S. DS courses are generally more accessible, with a third of universities offering them without prerequisites for early engagement. In contrast, AI and ML courses often require two to three semesters of prerequisites, suggesting they are advanced subjects for later study. Public universities usually have more prerequisites for these courses, which could present barriers to entry, particularly for students without a computing background, and potentially affect diversity and inclusivity in these fields. AI courses focus on programming skills, starting with CS1, while ML courses demand comprehensive preparation in programming and mathematics, indicating different foundational requirements and study depths for these subjects.

Our analysis emphasizes the need for educational strategies that balance foundational knowledge with accessible entry points into *AI* courses. The current trends observed in R1 institutions may not allow students early exposure to key AI areas and provide sufficient time for students to explore applications of these areas through research. As *AI* technologies continue to advance and integrate into various sectors, it is critical for educational frameworks to be flexible and ensure accessibility to students.

In conclusion, this study lays the groundwork for future research and curriculum development investigating the impact of the depth of prerequisites in creating accessible pathways in *AI* courses. By addressing the identified barriers, educational institutions focusing on students' research engagement can play a pivotal role in nurturing a well-prepared curriculum that encourages students' early research engagement in AI.

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