

Exploring the Impact of AI on Educators and Syllabus Policies

TEAM TAIP

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Contents

0 Abstract.....	3
1 Introduction.....	4
1.2 Effects of LLMs on Education.....	5
1.2.1 Beneficial Effects of LLMs in Education.....	5
1.2.2 Harmful Effects of LLMs in Education.....	6
1.3 The Importance of Personalized Learning.....	7
1.3.1 Challenges of Personalized Learning in the 21st Century.....	7
1.4 The Potential of AI Tools in the Classroom.....	8
1.5 Overview and Roadmap for Empirical Studies.....	9
2 Syllabi Review.....	9
2.1 Method.....	10
2.1.1 Syllabus Collection.....	10
2.1.2 Analysis Methodology.....	10
2.2 Results.....	11
2.2.1 Subject Area Analysis.....	11
2.2.2 Longitudinal Analysis of Education Syllabi.....	12
3 Survey - Middle School Math Teachers.....	15
3.1 Methods.....	15
3.1.1 Participants and Materials.....	16
3.2 Results.....	16
3.2.1 General Technology Results.....	16
3.2.2 AI Results.....	17
3.3 Discussion.....	19
4. General Discussion.....	20
4.1 Limitations.....	20
4.2 Implications and Applications.....	20
4.3 Conclusions.....	21
References.....	22
Appendix.....	31

0 Abstract

In this study, we examined the growth of Artificial Intelligence (AI) in higher education, supplemented by a survey on middle school teachers' perspectives. Over the past few years, AI has become increasingly common in the classroom and has sparked conversation about its harms and benefits. We analyzed university course syllabi from the University of Maryland spanning Fall 2022 to Fall 2025, which showed a clear trend towards allowing the usage of AI in the classroom, especially by students training to be future educators. Across our dataset, a requirement to cite AI usage was the most popular restriction on AI usage, indicating educators are increasingly willing to allow AI as long as its use is transparent. Adoption is not consistent across disciplines, with the humanities and education representing the highest observed adoption, and business and engineering representing the least adoption. Additionally, we performed a supplemental study, surveying middle school teachers and their opinions on AI in the classroom, where we explored educators' perceptions of AI and their willingness to adopt it in the classroom. Our survey results show that educators still are not sure of the potential use cases of AI in the classroom, but are encouraged by the possibility of reducing the workload. Future work should survey more instructors across more disciplines to get a more widespread opinion on AI in the classroom.

1 Introduction

Large Language Models (LLMs) have taken the world by storm due in large part to their ability to hold open-ended conversations with users. This was ignited by the introduction of the Transformer architecture, which showed strong results in language tasks while being faster and cheaper to train (Vaswani et al., 2017). Transformer-based models also show marked improvement with increased model size and training data, resulting in the powerful models that are available today (Hoffmann et al., 2022; Kaplan et al., 2020). While these models have genuine applications for assisting students in understanding course material, they also bring with them the real danger of cheating. LLMs are sufficiently advanced to the point where they can complete college-level programming projects, math worksheets, essays, and more with little to no effort from the student.

This provides a dilemma for professors: with the widespread adoption of LLMs, instructors are forced to consider their impact - both positive and negative - on student learning. Due to the problem-solving power of LLMs, professors must formalize how, when, and where students should be allowed to use AI by establishing clear policies within their course syllabi. For example, they may outright ban AI, allow full usage of AI, require citations of AI usage, and so forth. K-12 educators also must consider how recent advances in AI could impact personalized learning in the classroom.

As the adoption of AI becomes more and more widespread, there is an increased emphasis on finding new ways in which the technology can be used to benefit students and educators alike. The primary goal of this research is to observe the current state of AI adoption in both K-12 and higher education classrooms by looking at the degree to which teachers allow students to access AI across disciplines, and longitudinally since the recent widespread adoption of AI tools like ChatGPT. The goal of this is to analyze how college professors have altered their syllabus policies to adapt to the widespread accessibility of AI. To this end, we collected a dataset of university course syllabi dating back to Fall 2022. Furthermore, to explore AI's potential for a classroom of younger learners, we surveyed middle school math teachers about their experiences with AI in the classroom, and their opinions on AI tools in the classroom. By analyzing changes in college-level AI policies alongside survey feedback of middle school teachers, we examine how educators across different levels are responding to the rapid rise of AI. This leads to our following research questions:

1. How do university instructors adopt AI policies in their syllabi over time?
2. How do AI syllabi policies differ across different disciplines?
3. What features do middle school teachers need in AI-education tools that are currently missing?
4. What are some potential challenges in creating an AI-based application for middle school teachers?

1.2 Effects of LLMs on Education

1.2.1 Beneficial Effects of LLMs in Education

Researchers have devoted much effort to figuring out how LLMs could be applied in an education setting, especially given their ability to provide personalized learning experiences to every student. Search engines are easy to access, but results are restricted to already existing web materials. Teachers can skillfully work with students to address misconceptions and support their learning, but cannot possibly be asked to be available 24/7. LLMs, on the other hand, can be readily used from any device and provide real-time, contextual feedback to students. This combination of accessibility and personalization makes LLMs an attractive resource for students to use. If a student is stuck on a math problem, they can ask the LLM for hints to help them make forward progress. Similarly, if a student does not understand the material taught in class, they can try working with the LLM to illuminate those concepts for them. LLMs also have numerous applications for students ranging from summarizing key ideas in texts, empowering disabled learners, creating study plans, and testing student knowledge (Beale, 2025; Kasneci et al., 2023).

Learning platforms have already taken steps to tailor LLMs for student use to improve studying and learning outcomes. For example, Khan Academy's Khanmigo was created to teach students using the Socratic approach to force students to think critically instead of directly giving away answers (Beale, 2025; Shetye, 2024). State-of-the-art LLMs such as Gemini, Perplexity, Claude, and ChatGPT are often directly advertising to students, including via free trials, appeals to having a personal tutor, and even ready-to-use chat templates made by students (alexwanderson.d.; ChatGPT for students n.d.; Education | Claude n.d.; Gemini for students — your AI study buddy from Google n.d.).

LLMs are also used by teachers to create materials for their courses. For example, they can be used to create lesson plans, assessment questions, and examples (Beale, 2025; Hu et al., 2025). In this sense, LLMs could be viewed as interactive partners in preparing materials for class and a soundboard for idea generation. Much of the appeal in using LLMs, then, to assist teachers is that they can be used to speed up course preparation, give advice to improve the effectiveness of instruction, and ultimately save them time.

Teacher perceptions on the use of AI and LLMs in education are varied. In one study of 150 Nigerian educational psychologists, most respondents saw AI tools as useful for improving administrative efficiency, personalized learning, and student engagement, but that infrastructural challenges such as poor internet connectivity as well as the potential for resistance to change could negatively impact the adoption of AI tools (Ofoegbu et al., 2025). Another study on the application of AI tools in Malaysian elementary math classes found that many teachers appreciated the potential for AI tools to give personalized learning experiences and save teachers

time on grading and creating assessments. However, there were also concerns about the learning curve to use AI tools, difficulties in integrating AI tools with existing curriculums, and AI feedback being too generic and not sufficiently helpful (Song et al., 2025).

Despite the potential benefits that LLMs provide to both students and teachers, there is widespread concern about the dangers LLMs pose to student learning. In particular, LLMs sometimes have the issue of being too effective, enabling students to rely too heavily on them. This poses several major risks.

1.2.2 Harmful Effects of LLMs in Education

One of the biggest concerns regarding LLMs in the classroom is its potential for widespread cheating given how accessible LLMs are and existing educational incentives. If a student's sole goal is to get a high mark in their classes, then it may be tempting for students to have an AI agent complete their work for them, especially if they believe that it would perform better and save them time. AI content detection tools are not always accurate and are known to create false positives, allowing students to get away with cheating and penalizing unlucky students whose work is incorrectly marked as "AI-generated" (Deep et al., 2025; Elkhatat et al., 2023). In this sense, LLMs have made it even more difficult to ensure that students are evaluated fairly and sufficient countermeasures exist against cheating.

Furthermore, the potential for students to overrely on LLMs poses a pedagogical nightmare for teachers, both in secondary and higher education. If teachers are unable to tell if students genuinely completed their work, then it becomes impossible to tell whether they actually understand the course content. Overreliance on AI has been shown to lead to negative impacts on decision-making, critical thinking, and analytical reasoning as students look for "shortcuts" to do their work (Zhai et al., 2024). This could lead to a negative feedback loop in which, as coursework is scaffolded and becomes increasingly difficult, students feel forced to become more reliant on AI and learn very little as a result.

There is also the issue of AI hallucinations, which is when LLMs generate factually incorrect responses that can present as dangerously plausible (Naveed et al., 2025; Waldo & Boussard, 2025). While an expert in a given field may be able to quickly identify when an LLM strays from sensibility, it is far more likely for hallucinations to go undetected by students, who may not have sufficient knowledge to identify LLM statements that appear reasonable but are incorrect. Although strides have been made in the field of uncertainty quantification in the hopes of detecting and ultimately preventing AI hallucinations altogether, it is far from a solved issue (Fadeeva et al., 2024; Lin et al., 2024; Vashurin et al., 2025; Zhang et al., 2023). This is especially troubling given that students who become overreliant on AI will then matriculate into the workforce, during which hallucinations could result in fatal real-world consequences. For example, physicians that become overreliant on AI programs could make critical errors that jeopardize the lives of their patients (Hamilton, 2024).

It is clear that LLMs have genuine potential as personalized, easy-to-use and access “tutors” that can accelerate student learning. However, their ease-of-use and widespread adoption poses a severe dilemma for instructors. Teachers are forced to reckon with the numerous risks they pose, including enabling cheating, stifling critical thinking, and preventing true understanding of course concepts.

1.3 The Importance of Personalized Learning

Personalized learning is an instructional practice where “the pace of learning and the instructional approach are optimized for the needs of each learner” (U.S. Department of Education, 2016). The goal of personalized learning is to meet students where they are in the learning process so that each student’s education is tailored towards what would benefit them the most. There are a variety of learning theories related to personalized learning that have been shown in studies to have a positive impact on student engagement and learning outcomes, such as context personalization, which is the “incorporation of students’ out-of-school interests into learning tasks” (Bernacki & Walkington, 2018). While these learning theories warrant further research into how they could be implemented in AI tools in education, the area of personalized learning most relevant to this project is mastery learning, which is a metacognitive learning theory that emphasizes focusing on specific tasks or learning objectives for students based on the extent of their current knowledge and the use of detailed, frequent feedback to address students’ gaps in requisite knowledge (Bernacki et al., 2021; Kulik et al., 1990). Mastery learning has been shown in previous studies to improve student self-efficacy and exam performance, with more pronounced effects on students with lower competency in the course material when compared to their peers (Kulik et al., 1990). To achieve these effects, there are several recommended practices for implementing mastery learning, such as dividing learning into small chunks, providing numerous opportunities for practice, giving frequent assessments and feedback, and adjusting instruction to ensure that students who need more support are able to receive it (Johns Hopkins University, 2020). Practices such as these can be enhanced through the implementation of AI learning technologies, which can quickly perform complex tasks and analyze patterns in data to assist students.

1.3.1 Challenges of Personalized Learning in the 21st Century

In recent decades, there has been an effort to prioritize personalization in student learning in order to better suit each individual student’s needs (Zhang et al., 2020). However, this has been hampered in some ways by the widespread adoption of online learning and AI technologies. In one study based in England, researchers determined that the use of interactive whiteboards encouraged students to focus more on achieving correct answers rather than being willing to make mistakes and analyze them as learning opportunities (Kennewell et al., 2007). The direct, parametrized representations of student progress shifted students’ focus from their mastery of the course material to the score displayed on their screen. Many classrooms also suffer from having

large class sizes (and correspondingly high student-to-teacher ratios), which has been linked with increased difficulty in adjusting for each student's needs (Yelkpiri et al., 2012). Another study highlights the ethical concerns that many teachers and researchers have regarding the potential for the dehumanization of learning as education systems rely more and more on high-tech digital devices and programs rather than student-teacher relationships and “spiritual and moral competencies” that are not so easily parametrized (Kassymova et al., 2023). While there is certainly potential for AI technologies to improve the standard of education for students across the board, great care must be taken in mitigating the potentially harmful effects of their adoption and addressing the already documented flaws of online learning systems.

1.4 The Potential of AI Tools in the Classroom

Before surveying teachers about their sentiment towards AI platforms in the classroom, we must understand the potential benefits these AI tools could provide. These benefits include increased personalization of learning, development of responsive resources, greater customizability of curricular resources, and greater support for teachers (Cardona et al., 2023). The viability and usefulness of creating an AI application has been demonstrated in various case studies, some of which have been discussed previously. An example is when Khan Academy introduced Khanmigo in March 2023, an experimental AI guide that limited users had access to (Grace, 2023). Khanmigo already has many possible uses in Khan Academy. In the past, teachers had to write their own lesson plans; now Khanmigo is able to help them with this. In addition, students can debate topics online on Khan Academy where the Khanmigo AI takes the other side to help them with their arguments and practice (Grace, 2023).

Another example is the study exploring the effects of utilizing Smart Learning Partner (SLP), an AI-aided education platform used in Chinese schools. The results of the study showed that there were considerable benefits that were gained by using the application for both students and teachers (Niu et al., 2022). For the students, the instant feedback they received from the platform and their learning analysis reports were extremely valuable, as they could track their own progress and gain the ability to gauge how well they were doing in the class. In addition, the mini lectures that could be accessed based on the student's interests, needs, or suggestions allowed for self-paced supplemental learning that could synergize with classroom instruction. For the teachers, the students' learning analysis reports helped them understand their students' learning situations more thoroughly, which helped them prepare more personalized lessons for the students. The mini lecture function could be used by the teachers for lessons or for recommendations to the students for further study. The assessment tools provided by SLP could be used for diagnostic purposes and homework assignments. Coupled with the auto grading function, this helped reduce teacher workload (Niu et al., 2022).

1.5 Overview and Roadmap for Empirical Studies

Our research includes two complementary empirical components designed to examine the current role and perceptions of AI in education at different levels: a University of Maryland syllabi review and a survey of middle school math teachers. Together, these studies provide insights on how AI is being integrated into classrooms, both from the perspective of educators who are implementing new tools and from the policy standpoint of institutions that are setting guidelines for their use.

The syllabi review is intended to help understand how professors respond to the widespread adoption of AI in their syllabi to reveal how these attitudes are formally expressed or neglected in university policies. By collecting and analyzing hundreds of syllabi from across departments at the University of Maryland, we track the evolution of AI-related policies since the public release of ChatGPT in late 2022. This longitudinal dataset allows us to quantify the growing presence and permissiveness of AI in higher education, offering a unique lens on how institutions respond to technological change.

The teacher survey explores how educators perceive AI's potential to reduce workload and enhance teaching effectiveness, as well as the obstacles that limit adoption. Conducted through outreach to middle school math teachers across the United States, the survey provides insight into teachers' comfort levels with AI, their prior experience, and their most pressing concerns, such as accuracy, privacy, and misuse. Although limited in sample size, the data highlight clear trends: teachers are optimistic about AI's potential to save time and improve instruction, yet remain uncertain about reliability and classroom control. This qualitative feedback guided our thinking about what features and safeguards should be prioritized in the design of future AI tools for education.

Conceptually, these two studies show both small-scale and large-scale views of AI use in education. The syllabi review shows larger policy changes happening at the university level, while the teacher survey highlights individual opinions and everyday classroom challenges with future university students. Together, they help us understand both bottom-up and top-down effects: how those policies can guide what happens in classrooms, and how teachers' real experiences can shape school policies.

2 Syllabi Review

The syllabus provides a space for instructors to indirectly communicate their opinions on AI in education. Even a lack of mention to AI in a course syllabus is valuable in showing the lack of emphasis from the professor in confronting this new technology, or a lack of knowledge about how to appropriately address AI in their course syllabi. Furthermore, generative AI achieved widespread popularity relatively recently, so there are bound to be varying approaches instructors have taken to address their widespread use. By systematically analyzing course

syllabi, we attempt to quantify these opinions and uncover trends in AI policy adoption. In this section, we detail the collection and results of analyzing cross-departmental and longitudinal syllabi from the University of Maryland. We establish a framework for analyzing syllabi and use it to observe differences in AI policy adoption across departments, as well as the change in policy over time, through a case study of a single department.

2.1 Method

2.1.1 Syllabus Collection

In this study, we collected data through interactions with University of Maryland faculty and by manually collecting syllabus data publicly available on the UMD Course Schedule at <https://www.testudo.umd.edu/>. In total, we collected 353 syllabi from the Fall and Spring 2025 semesters at the University of Maryland. We also collected longitudinal data for the Department of Teaching and Learning, Policy and Leadership (TLPL) department, encompassing 385 syllabi dating back to Fall 2022, to observe the rise in AI usage in the classroom.

2.1.2 Analysis Methodology

Whereas the analysis in (Ali et al., 2024) took a highly granular approach to analyzing syllabi across universities, we noticed a high degree of overlap in language between the syllabi in our data. This stems from specific AI-usage templates promoted by the university (Sample syllabus language - artificial intelligence policies, n.d.), and varying from full restrictions of AI in the classroom to full allowance. To remedy this, we define a spectrum of AI based on the university template suggestions, and categorize each syllabus into one of 5 categories.

Each syllabus was analyzed by one of a group of 5 reviewers. For each document, the course name, instructor name, course code, and course semester were collected. Next, the exact portion of the syllabus regarding AI usage in the classroom (if applicable) was collected. Finally, the level of AI usage allowed was recorded, divided into the following categories:

1. AI not mentioned in syllabus
2. AI strictly prohibited
3. AI allowed, with defined limitations
4. AI allowed with defined limitations, and encouraged
5. AI allowed completely without defined limitations

We selected these categories to reflect instructors' overall attitudes toward AI. In particular, distinguishing between merely allowing AI with limitations and actively encouraging its use highlights a shift from viewing AI as a challenge that must be managed through policy to recognizing it as a valuable educational tool.

We also delved further into the specific limitations imposed on the utilization of AI tools, breaking down limitations by the following categories:

1. **Citation Required** - Any AI use must be clearly cited in the assignment (e.g., “This draft was generated with assistance from ChatGPT”).
2. **Brainstorming Only** - AI may be used for brainstorming, research support, or defining complex terms, but not for writing final drafts.
3. **Assignment-Specific** - AI use is only permitted when explicitly allowed in the assignment instructions OR AI is only permitted in some assignments.
4. **Other** (to be selected if the restriction does not fit neatly into the previous categories)

2.2 Results

Of the 353 collected syllabi for Fall 2025, a majority contained some mention of the place of Artificial Intelligence in the classroom (199 / 353, 56.37%). Of those syllabi, a majority allow some degree of integration of AI in course curriculum (121 / 199, 60.8%). Of the 114 courses that allow the usage of AI with defined limitations, the dominant limitation is Citation Required, as shown in Figure 1.

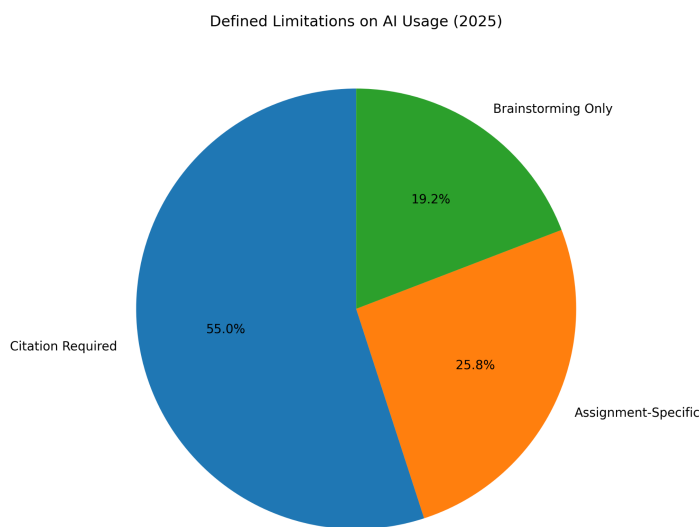


Figure 1: Breakdown of AI Usage Limitations

2.2.1 Subject Area Analysis

To address the degree to which different subject areas have adopted AI policies in their course syllabi, we partitioned our data based on subject categories. We selected the categories of Business, Education, Engineering, Humanities, Natural Sciences, and Social Sciences. We then divided our data based on 4 character department names as listed in the course codes. More details of the departments selected for each category are located in Appendix 1. A breakdown of

AI adoption by subject is located in Figure 2, and demonstrated the high rates of adoption in Education and humanities, while comparatively low rates of adoption in business and engineering.

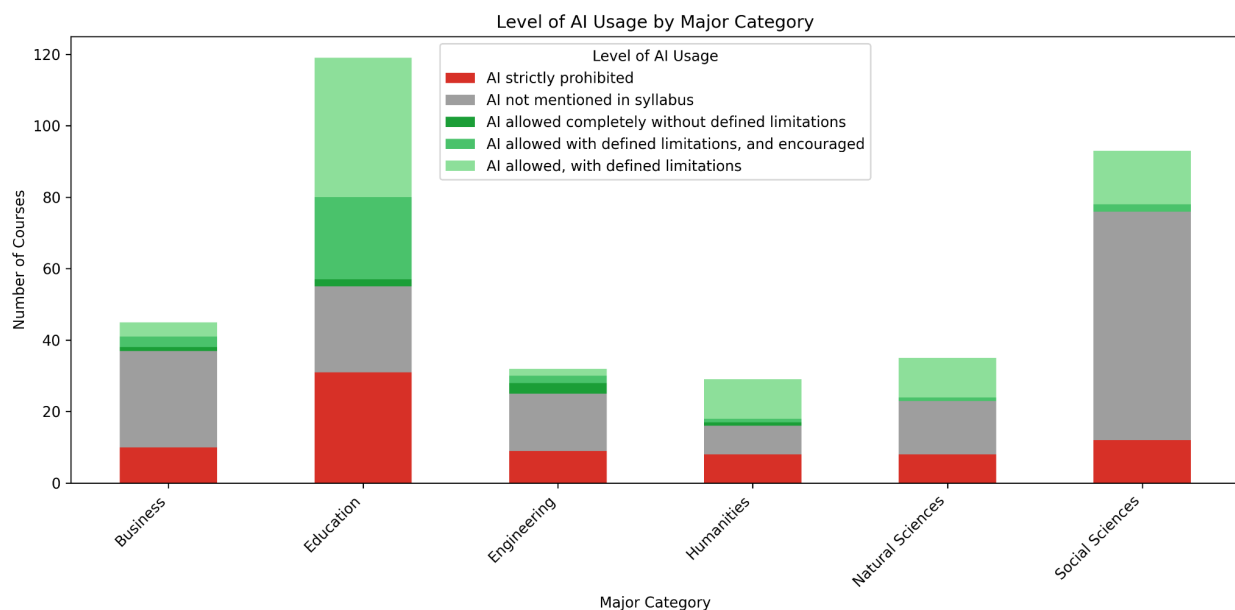


Figure 2: Level of AI Usage by Major Category in Spring and Fall 2025 semesters.

2.2.2 Longitudinal Analysis of Education Syllabi

In this section, we conducted a case study on the Department of Teaching and Learning, Policy and Leadership syllabi. TLPL’s mission is to “encourage thoughtful and responsive explorations of education policies, practices and related social issues” (*TLPL | UMD College of Education*, n.d.). Courses in the department consist of education on education policies, education on teaching methodologies, and semester-long internships at schools. Looking at the reaction of TLPL to AI in education over time is a valuable tool for understanding how future educators and policymakers are being prepared to engage with emerging technologies.

We analyzed TLPL syllabi from Fall 2022 to Fall 2025. This places our data before the release of ChatGPT on November 30, 2022, allowing us to view the rise of AI policies in syllabi (*Introducing ChatGPT*, 2022). While the data only represents a single department’s policies, it is valuable in showing the rise of AI policies in college course syllabi, and provides a framework to analyze more departments.

Our TLPL dataset contains 385 unique syllabi representing 221 courses and 150 instructors (Figure 3). The Fall 2022 semester syllabi were released in September of 2022 (Division of academic affairs, 2024), explaining the absence of any AI related policies. By Fall of 2025, 57 of 61 syllabi contained some reference to AI in the course syllabi. We utilized this

data to answer the following research questions regarding the rise of AI in university course syllabi:

1. How has AI policy in course syllabi changed over time?
2. Have instructors changed their minds on AI?

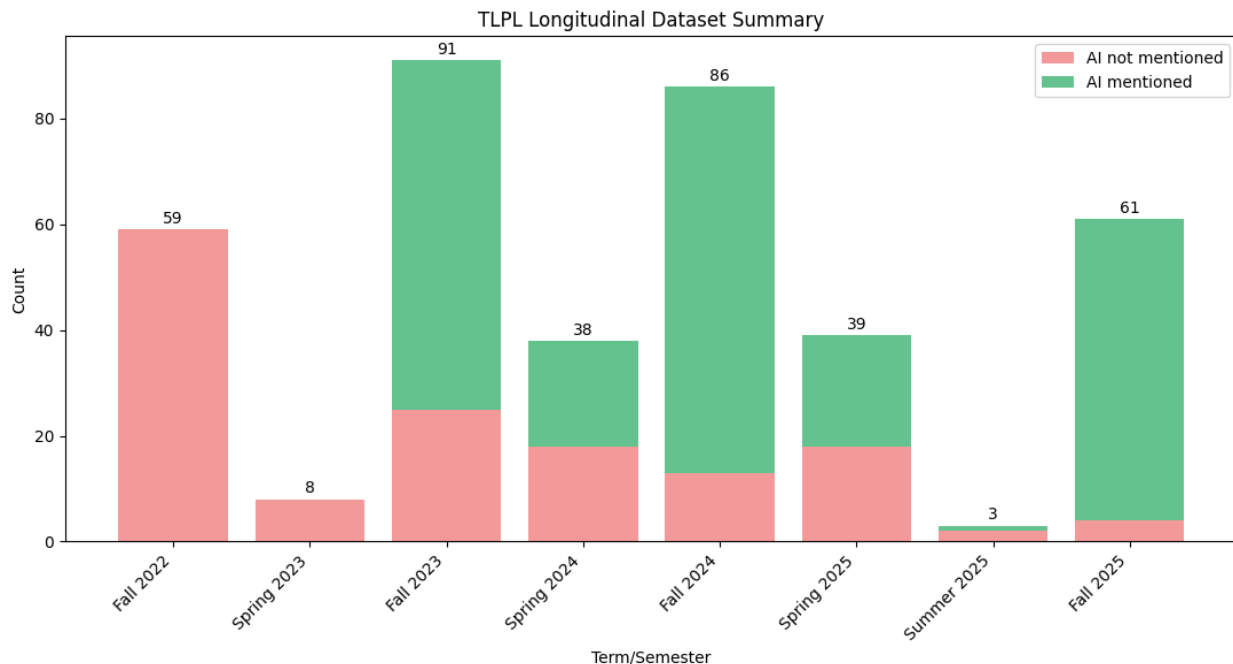


Figure 3: Summary of TLPL Longitudinal Dataset

Our results clearly indicate a shift towards the adoption of AI in the classroom (Figure 4). In Fall of 2025, 72.88% of syllabi allow for some degree of AI usage in the classroom, a 113.44% increase from Fall 2024. A breakdown of the kinds of restrictions on AI usage in courses where AI is allowed (Figure 5) shows that a requirement to cite AI usage is the most prominent restriction, totalling 60.75% of courses that allow AI with limitations. The following is an excerpt from one such syllabi, showing the template commonly adopted for Citation Required:

“When you use these tools, it is your responsibility as a scholar to make sure you are clearly communicating the AI involvement in your work. Please make sure to use phrases such as “[your name] via DALL-E 2” (for images) or “This paper was generated with the help of GPT-3” (for essays).”

Since 2024 there has also been a rise in Brainstorming Only restrictions, showing greater acknowledgement and support for the potential role of AI tools in the research and thought development process over time.

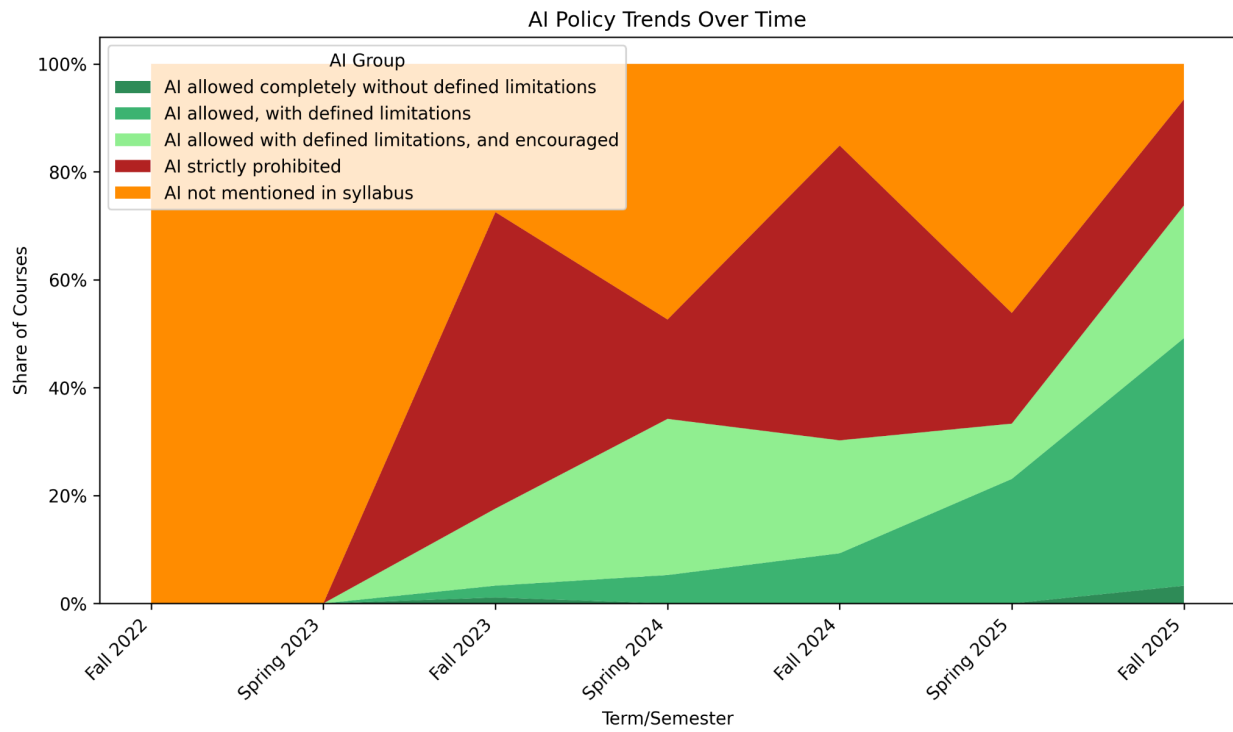


Figure 4: Change in AI policy adoption in the TLPL department from Fall 2022 to Fall 2025

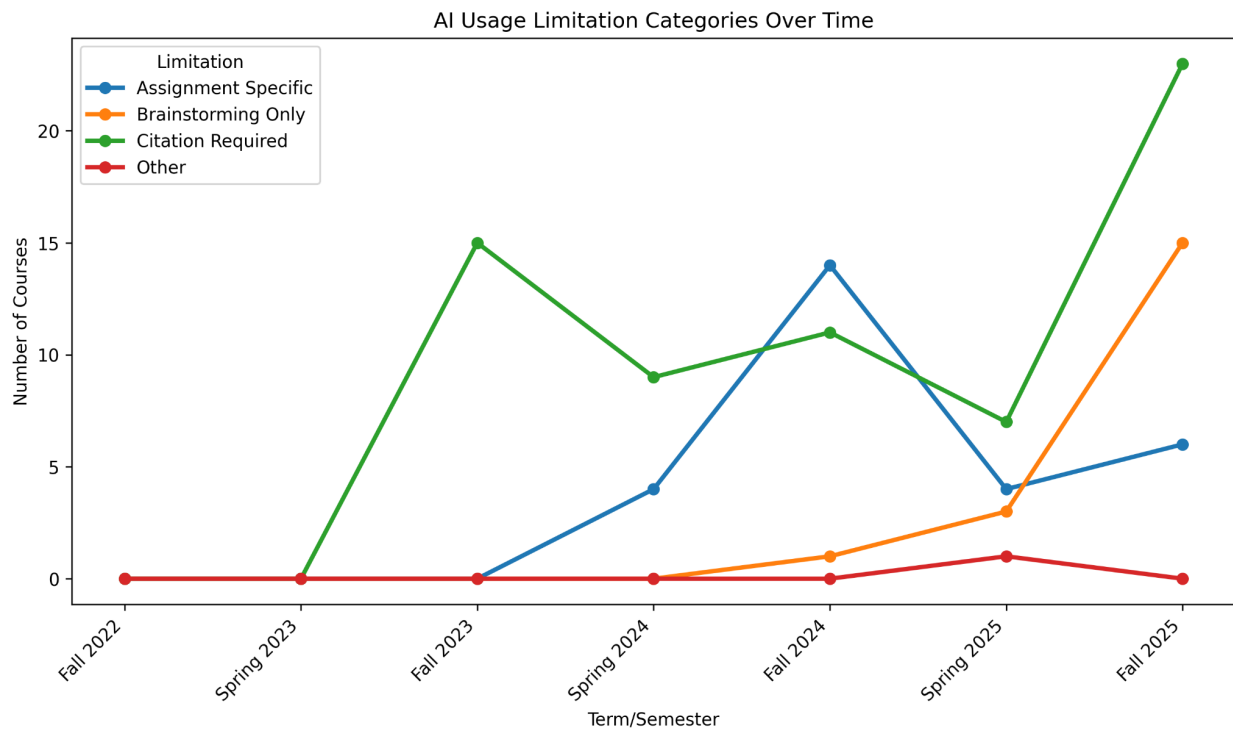


Figure 5: Breakdown of limitations of AI usage imposed by instructors, Fall 2022 to Fall 2025

3 Survey - Middle School Math Teachers

The goal of this project was to learn more about what teachers may want in an AI platform to inform future creators. The research design for this project was a mixed-method approach that combined both quantitative and qualitative research methods to gauge the usefulness of an AI application in the classroom. This approach was chosen in order to gather a comprehensive understanding of the impact an AI-based application can have on teachers' practices and workloads.

3.1 Methods

Participants were emailed the Qualtrics survey link. It began with a consent form, then continued with questions about AI in the classroom. The survey ended with a question about participants' interest in compensation and future work with us. If the participant answered no, the survey ended there. If the participant answered yes, they were redirected to a second survey that asked participants for their name and email in order to compensate them.

The participants in our study were teachers from the United States. Participants were recruited through a convenience sample of teachers known personally to us, through school directory data, and over social media. A raffle incentive was offered to encourage participation in the study. After a long recruitment process, 13 people filled out our survey. All were middle school math teachers who taught between 6th grade and 8th grade. There was a range of teaching experiences from 2 years to more than 30 years.

3.1.1 Participants and Materials

Surveys were distributed to teachers to collect their opinions and feedback on the current state of AI usage in their classroom, and what could be implemented in a future AI-based application. The teachers were given descriptions of current AI applications and asked to describe what they find appealing about the applications and what the applications may be missing. Participants were asked what they would like to see in future AI-based applications for teachers that would better assist them in teaching. The questions asked were as follows:

- ***Past Use and Prior Knowledge:***
 - In your experience, to the best of your knowledge, how would you say students have used AI in the classroom?
 - Have you ever used AI tools (e.g. ChatGPT, Khanmigo, DeltaMath) in your classroom?
 - If yes, what did you like most about it and what did you think needed improvement?

- On a scale of 1-10, with 1 being ‘not comfortable at all’ and 10 being ‘extremely comfortable’, how comfortable do you feel with using technology, and more specifically AI, in your daily life?
- **Potential Uses:**
 - What do you see as the most exciting uses of AI in the classroom?
 - What is currently the aspect of your workload that takes the most time for you to complete?
 - What would be the most useful feature(s) to you in an AI tool?
 - On a scale of 1-10, how much do you like the idea of using an AI tool to help lighten your workload?
- **Potential Challenges and Concerns:**
 - What are your biggest concerns about the use of AI in the classroom?

3.2 Results

The small sample size of our data allowed for detailed qualitative analysis of teacher responses. Each response was sorted by similarity on metrics including hardware used in the classroom, general AI participation, and sentiment towards increased AI usage in the classroom. This section highlights the similarities and differences between the answers of participants.

3.2.1 General Technology Results

When asked about technology in their schools, 11 of the 13 teachers stated that their schools have Chromebooks. Chromebooks were the most common classroom technology mentioned (6 out of 13 participants). 4 out of 13 answered smart boards. There were 20 websites or devices that were stated by 1 or 2 participants. When asked which of these technologies the participants use at home, 9 out of 13 said None.

3.2.2 AI Results

When asked about what AI technology the participants use at home, 8 out of 13 said ChatGPT, and 3 out of 13 said “None”. When asked how participants think students use AI, 4 out of 13 said to complete assignments, and 4 out of 13 said that they are not sure.

When asked if the participants had ever used AI tools in the classroom, 5 of the 13 teachers said no, and 8 said yes. When asked what these tools were used for, 4 out of the 8 who reported yes said they use it for parent communication, and 6 out of the 8 said it helps with question making.

When asked about their favorite part of AI and what needs improvement, there was no overlap in response. When asked about what excited them about AI in the classroom, 10 out of 13 teachers said some form of lesson planning and problem writing. 3 out of 13 put N/A.

When asked what time-consuming aspect participants believe could be completed by AI, 4 out of 13 said practice problems, and 3 out of 13 said grading. 2 out of 13 gave negative responses to that question, explaining why AI may not be as good at lesson planning or study guides as others may think (Figure 6).

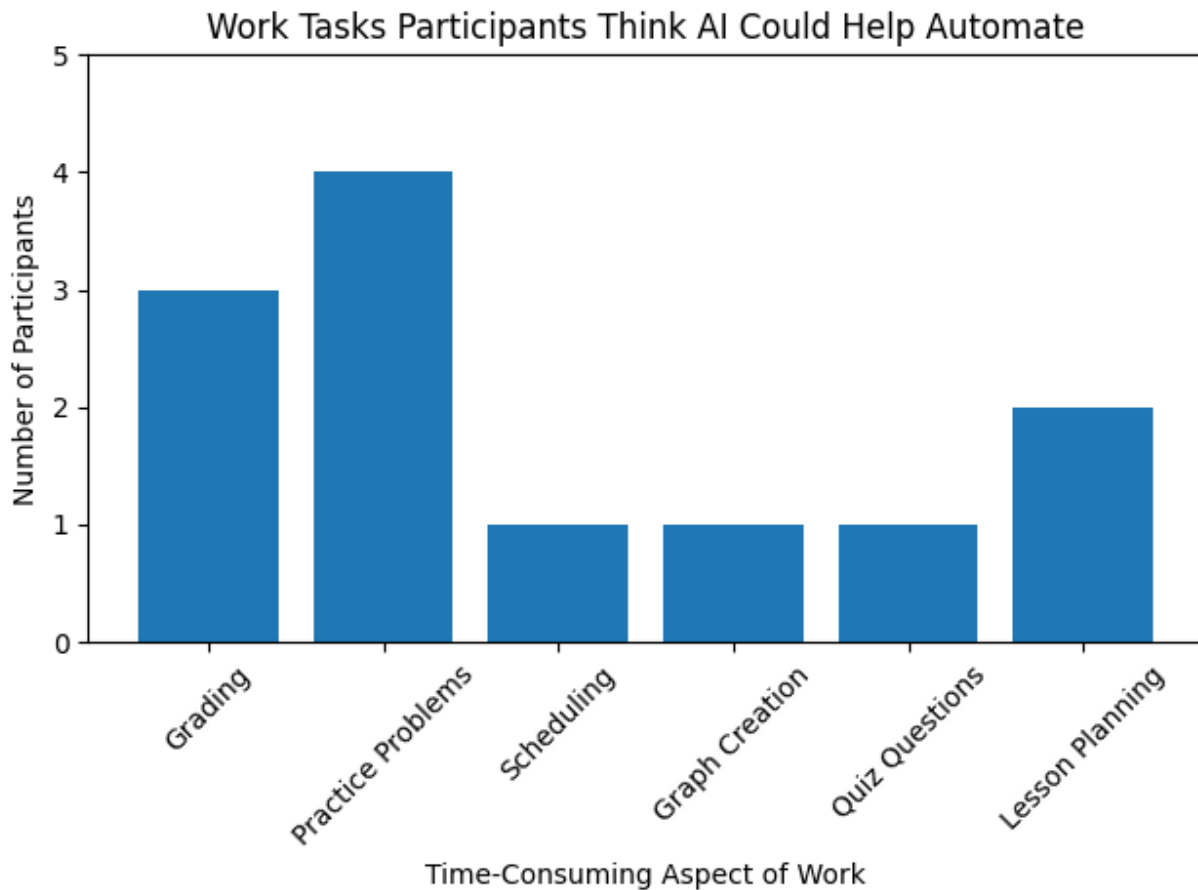


Figure 6: Participant response rate of time-consuming aspects of work that can be facilitated by AI

When asked what feature would be most useful in an AI tool, 3 out of 13 participants answered “Not Sure.” There were many other answers that were said by 2 participants or fewer, including grading, easy to learn, lesson planning, and worksheet generation.

When asked on a scale of 1-10 “How much do you like the idea of using an AI tool to help lighten your workload in the ways you have described above?” the lowest numbered response was 6, and the highest numbered response was 10. The average response was very positive, with a mean of 7.9 (Figure 7).

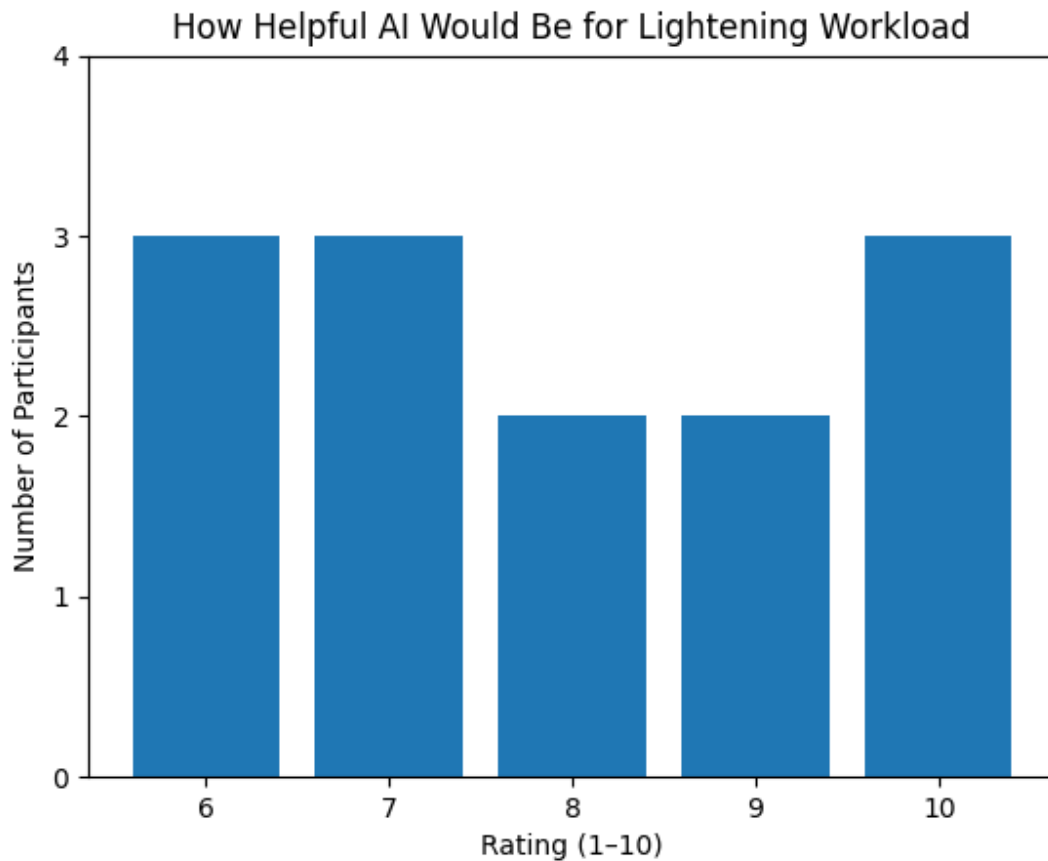


Figure 7: Participant response rate of interest in an AI tool that can lighten workload.

When asked about the biggest concerns of AI in the classroom, 7 out of 13 said correctness/accuracy/time it takes to correct it. 6 out of 13 said misuse of it in the classroom, 4 out of 13 said privacy concerns, and 3 out of 13 said over-reliance on tools. Lastly, when asked what limitations exist with AI, 4 out of 13 answered “knowledge”.

3.3 Discussion

On the general technology questions, it is clear that of the schools we surveyed, the majority have access to Chromebooks and use a range of tools for their education. Most teachers in the survey have used ChatGPT at home and have experience with it. The teachers in the

survey do not have a clear idea of what AI is being used for at this moment by students in the classroom, but many have used some form of AI in their classrooms. These tools have helped with parent communication and question making.

There is no overall agreement on the pros and cons for an AI platform, because each individual had their own thoughts and concerns. Some participants have a fear of AI not being accurate or it being misused by students, but this was not a concern expressed by all participants. There is a wide range of what the teachers want to use AI for, with lesson planning being the most common, but study resources and feedback seem helpful as well.

If one were to create an AI platform, it seems that the teachers would most want it to develop practice problems or grades for them, but there is no overall agreement on what the teachers would want AI to do. There was a unanimous positive response to having AI lighten the workload in some way. Finally, there were shared fears with AI, such as accuracy, privacy, and misuse.

AI tools could be a valuable asset to classrooms, but it will take trial and error to figure out what is best for teachers. It is clear that the participants in our study would be interested in AI helping with workload concerns, but that they do not have much experience using it themselves in the classroom. This creates room for opportunity for future AI platforms to help teachers where they may need it the most.

4. General Discussion

4.1 Limitations

The main limitation of the data collected for Study 1 is that it is a convenience sample. It is from the Department of Teaching and Learning, Policy and Leadership at the University of Maryland, or from students at the University of Maryland sending in their syllabi. This gives a good picture of the syllabi at the University of Maryland, but there are some underrepresented departments, such as Humanities and Engineering, and it does not represent other schools. Furthermore, we were only able to get detailed longitudinal data from TLPL, and were unable to analyze syllabi changes over time for other departments.

There are also notable limitations to this data from Study 2, and future work should be conducted to understand more about teachers' perspectives on AI in the classroom. This research was a good start to understanding the landscape of AI in the classroom, but the limited sample size makes it difficult to make sweeping claims about teachers' mindsets. Furthermore, this research was conducted as AI was becoming more popular, so while it has the advantage of getting participants' initial views of AI in the classroom, it is unclear to what extent those views hold true today.

4.2 Implications and Applications

Study 1 encompasses a systematic exploration of AI sentiment in course syllabi over time and across disciplines. We suggest future analysis of syllabi as a method of measuring instructors' perceptions of education policy as the field of education continues to change at a rapid pace. For Study 2, more research should be done that asks similar questions to delve deeper with a bigger audience to fully grasp the impact of AI in the classroom. Additionally, this research and future research could be used to help develop more AI tools that lighten teachers' workload.

Students and teachers' access to AI tools in middle school education could jumpstart personalized learning as explored in our survey analysis, but it also carries the risk of delaying mastery of subjects due to overreliance on AI technology. These students may then enter higher education without the necessary tools to succeed. Looking at higher education syllabi and AI policies alongside middle school classroom data, gives a full picture of the skills that students are expected to have in higher education and the technology that may hinder those skills.

4.3 Conclusions

The goal of our syllabus analysis was to understand the trends of AI in higher education. Our analysis of syllabi revealed the growing acceptance of AI in the classroom, specifically among students preparing for careers in education. The most common stipulation across the courses was the requirement of citing their AI-generated work. Therefore, instructors are increasingly open to AI if it is used transparently. The adoption varies by the discipline, where the humanities and education show higher levels of AI integration, while engineering and business reveal the lowest.

Study 2 aimed to look at middle school teachers' experience with AI in the classroom and their thoughts and concerns about an AI platform to be used in the classroom. Overall, our research suggests that it is clear that the teachers in this survey would have an interest in AI to lighten their workload, despite the possible concerns with it. It is not clear, however, what that AI platform would do. Together, these two sides of our research show an overall picture of AI in the classroom, both in middle school and higher education settings.

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Appendix

Category	Major Codes
Engineering	ENAE, ENBC, ENCE, ENEB, ENEE, ENES, ENFP, ENMA, ENME, ENRE, ENSE, MATH, AMSC, MSML, STAT, QMMS, CMSC, INST, INFM, DATA, MSAI, BIOI
Natural Sciences	CHEM, CHPH, CHBE, BIOL, BSCI, CBMG, ANSC, NFSC, ENTM, ENST, ENSP, MIEH, PHYS, BIPH, PSYC, NACS, NEUR
Humanities	ENGL, HNUH, HONR, CMLT, IMDM, JOUR, ARAB, CHIN, FREN, GERS, GREK, HEBR, ITAL, JAPN, KORA, LATN, PERS, PORT, RUSS, SPAN, ISRL, JWST, SLLC
Business	BMGT, BUAC, BUFN, BUMK, BULM, BUDT, BUSI, BUSM, BUSO, BMSO, HBUS, BMIN
Social Sciences	GVPT, FGSM, CPSS, CPJT, CPPL, CPCV, PLCY, HIST, ECON, SOCY, BSOS, ANTH, COMM, GEOG
Education	EDHD, TLPL

Table 1: Description of each category by UMD Department codes.