

Modern physics courses: Understanding the content taught in the U.S.Alexis Buzzell¹, Timothy J. Atherton², and Ramón Barthelemy¹¹*Department of Physics & Astronomy, University of Utah, Salt Lake City, Utah, USA*²*Department of Physics & Astronomy, Tufts University, Medford, Massachusetts, USA*

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The modern physics course is a crucial gateway for physics majors as it provides an introduction to concepts beyond the scope of the K-12 education. This study collected 167 modern physics syllabi from 127 U.S. research-intensive institutions using publicly available syllabi (51.5%) and private correspondence (48.5%). Due to the size of the corpus being large enough for natural language processing (NLP) to provide significant insight into the curricular content of a course, but still being small enough for human analysis to remain feasible, both NLP and human-analysis methods were utilized. The use of both methods provided a way to test the newly introduced method of NLP in physics education research and offered a novel tool for cross-validation. Public course catalogs were consulted to identify prerequisites and corequisites with 89.3% of students having completed a course in calculus II or higher. Foundational topics like Newtonian mechanics (94%), electricity and magnetism (84.4%), and waves or optics (77.2%) were frequently required. Most institutions consistently taught quantum physics (94%), atomic physics (83%), and relativity (70%), but there was variability in the inclusion of other topics alongside these three main topics. The study highlights the current modern physics curricula at U.S. research-intensive institutions, emphasizing the importance of a consistent and comprehensive education for physics majors across universities. This insight contributes to the ongoing discourse on optimizing physics education in higher education.

DOI: [10.1103/PhysRevPhysEducRes.21.010139](https://doi.org/10.1103/PhysRevPhysEducRes.21.010139)**I. INTRODUCTION**

The modern physics course serves as a pivotal gateway for students pursuing a physics major by introducing them to new material, beyond the scope of their K-12 experience, early in their undergraduate career [1]. Despite its significance, there exists variability in the topics covered, both across different institutions and with multiple versions of modern physics courses being offered at the same institution. Achieving uniformity across institutions is crucial to ensuring that students receive a standardized and comprehensive education to adequately prepare them for advanced studies and future careers, regardless of their undergraduate institution.

The variability in curriculum highlights the need for a thorough examination of the instructional materials used in modern physics courses to better understand these inconsistencies. A course's syllabus offers a rich dataset that outlines the expectations of both students and their instructors throughout the course. Instructors set the tone

for the course by outlining important details, such as the topics to be covered, how final grades will be calculated, and policies that may be of concern to students during the course. Requesting syllabi from instructors was a relatively low time commitment task to complete, while the data obtained from the collection of syllabi are immense. This paper presents a comprehensive analysis of 167 modern physics syllabi from 127 research-intensive institutions and identifies the most commonly taught topics across the U.S.

The size of the corpus facilitated the use of both natural language processing (NLP) and human analysis methods. The corpus is large enough for the NLP method to be able to determine latent themes within the textual syllabi data. Conversely, the corpus is small enough that human analysis methods are feasible. The use of both methods of analysis offered a unique opportunity not only to test the method of NLP in physics education research (PER) but also to offer a crucial layer of validation for our human analysis. With the use of artificial intelligence (AI) methodologies being introduced in PER, it is important to field-test the technology using a low risk dataset such as the one in this study. The complementary nature of NLP and human analysis ensured a robust validation process, with each method enhancing the reliability of the other.

The goals of this paper are to explore the diversity and consistency in the content of modern physics courses across research-intensive institutions in the U.S. and to

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evaluate the potential of NLP as a cross-validation tool in physics education research. By analyzing 167 syllabi from 127 institutions using both human-coding and NLP methods, the study aims to identify commonly taught topics, assess pedagogical approaches, and investigate the prerequisites for these courses.

II. LITERATURE REVIEW

A. Education research on the modern physics course

Discussions around the need for better alignment between modern physics courses and the more advanced quantum mechanics courses have taken place since 2001 [2]; Singh *et al.* argued that the semiclassical models learned in modern physics courses can give rise to misconceptions students must overcome later in their quantum mechanics courses [3]. The Bohr model is one such example of a semiclassical model. Singh found that instructors of quantum mechanics courses had to spend course time “unteaching” the Bohr model to their students [4]. Modern physics courses need to place an emphasis on both the limits and the appropriate applications of the semiclassical models learned. Vokos *et al.* [5] stated that an instructional goal for modern physics is for students to be introduced to quantum concepts at the level of understanding wave-particle duality. This message is echoed by Singh *et al.* [3], who stated that most physicists were introduced to quantum mechanics during their modern physics courses as undergraduate students. However, neither statement provides empirical evidence for this claim; hence the need for this study to investigate what topics are taught in modern physics courses within the U.S. and determine when these undergraduate students were first exposed to quantum concepts.

Other research on modern physics has predominantly focused on students’ misconceptions about physics and on the development of their understanding of quantum mechanics. Researchers have explored students’ ontological and epistemological shifts as they transition from a classical physics perspective to a quantum perspective [6,7]. Investigations have also delved into challenges related to learning quantum tunneling [8] and the challenges related to the development of assessment tools to evaluate the conceptual and visual understanding of quantum mechanics [9].

In response to the diverse needs of students, particularly engineering majors, reforms have been implemented to tailor modern physics curricula to these students by emphasizing real-world applications over abstract problems [10]. Arguments have also been made for introducing modern physics topics earlier in the physics education, either at the high school or lower undergraduate levels [11,12].

Some scholars have focused on instructor perspectives on the modern physics course. An informal survey

conducted via *The Physics Teacher* (December 2013 edition) and the 2014 Oersted Lecture sought opinions on essential introductory modern physics topics [13]. Quantum mechanics and special relativity were considered crucial, while thermodynamics and rotational dynamics were suggested for omission. This current study builds off Zollman’s informal survey by providing a detailed analysis of the topics taught in modern physics courses.

B. Literature on STEM syllabi

When considering how to best determine the topics taught across modern physics courses, syllabi readily surfaced as a feasible option. Syllabi served as a valuable tool to obtain course content without requiring significant time commitments from the course instructors. However, syllabi also reflect instructors’ and institutions’ values within the science, technology, engineering, and math (STEM) fields [14]. Syllabi, beyond structuring learning outcomes and course objectives, communicate expectations between instructors and students. Epistemological beliefs embedded in syllabi impact pedagogical approaches. The language used in syllabi is crucial, as studies have shown that a chilly climate in the classroom, characterized by a male-normed, highly impersonal, and individualistic environment, can lead to women changing their majors to non-STEM fields.

C. Artificial intelligence methods in PER

To complement the human-coded analysis, this study performed an analysis of the collected data using AI and NLP techniques. Driven by the availability of new technologies for automating the processing of large textual datasets, there has been an emerging interest in applying such methods to data collected in PER studies, and more broadly, in higher education [15]. Many algorithms are available to solve a variety of tasks [16,17], falling broadly into *supervised* techniques, where a set of training data must be provided to the algorithm, and *unsupervised* techniques that discover structure without human supervision. To situate our work, we provide a brief snapshot of how NLP methods are already being applied in PER before turning to our analysis.

One possible application domain is to analyze student work. Wilson *et al.* created classifiers for free responses to the Physics Measurement Questionnaire [18] that performed with similar reliability based on two human coders. The researchers, however, urged caution in using such approaches in the classroom due to the possibility of biases in the classifier or in the training set. Similarly, Campbell *et al.* [19] used the Watson NLP to classify whether certain conceptual themes were present or absent in short-answer student responses.

Another NLP task is to identify latent themes within a textual corpus. Odden *et al.* [20] examined the contents of all PER conference proceedings and some 1300 short

papers written between 2001 and 2018 to resolve emergent topics including when they appeared over time. The same authors have further refined their method [21]. Such methods may be particularly appealing for scaling qualitative research studies, in particular, because qualitative studies tend to generate large quantities of text, through transcripts or survey responses, that can be time consuming to analyze. Tschisgale *et al.* recently advocated for incorporating NLP methods to facilitate theory building in qualitative studies [22].

A third possibility is to use AI tools to generate or answer physics problems. Large language models (LLMs), notably ChatGPT, have attracted considerable private and public attention because they generate naturalistic answers to questions posed in human language. Multiple studies have found that ChatGPT is capable of generating convincing answers to the Force Concept Inventory [23,24]. However, Dahlkemper *et al.* found that students could distinguish ChatGPT-generated answers to physics problems from instructor-generated answers, but only if their subject knowledge was adequate [25]. LLMs have also been demonstrated as part of a system intended to grade student work [26]. Nonetheless, the use of NLP in such contexts raises a number of important ethical issues, due to biases in training sets and algorithmic features [27].

While AI methods are relatively new to PER, the corpus of syllabi obtained for the present study presents an attractive target for AI methods because the corpus is large enough to provide significant insight into the curricular content of a course that is taught in almost all physics departments, but small enough that human analysis remains feasible. Applying NLP to curricular-level research, as opposed to student work or to understanding PER itself, appears to be a new application of these methods and therefore may become a useful tool for further studies. Like Odden *et al.* [20], we believe that “[NLP] cannot replace careful analysis by humans” and that “validation is very important.” Hence, we chose to use a multimethods approach, centralizing human coding while supplementing and validating this with an exploratory NLP analysis.

III. METHODS

A. Human-coding methods

Syllabi were collected from the institutions listed in U.S. News Rankings of “The Best Physics Programs” [28]. This list ranks mostly research-focused physics programs that offer a graduate-level physics education. We chose to focus on this community of schools as they are producing the next generation of physics faculty and have been shown to educate more than half of the physics students in the U.S. [29]. This list ranks 190 institutions, 188 of which offer a 4-year physics degree. In the year 2021–2022, these institutions cumulatively granted 4772 bachelor’s degrees or 56.7% of the bachelor’s degrees in physics granted in that

year. The authors recognize these institutions may not be fully inclusive of all students across physics education; however, we put a significant focus on institutions serving students from diverse backgrounds in our analysis.

Of the 190 programs listed in the ranking, 181 offered a modern physics or equivalent course in their publicly available course catalog. Of the 181 programs, syllabi were collected from 70.2% resulting in 127 institutions being represented in the dataset. Some programs offered more than one modern physics course to their student body resulting in a total of 167 syllabi obtained from the 127 institutions.

Within the set of 127 institutions, 78% were classified as having very high research activity, 20% were classified as having high research activity, and 2 institutions were not classified in the Carnegie Classification of Institutions of Higher Education [30]. About 73% were public institutions [30]. The syllabi were collected using public online searches (51.5%) and private email communications with instructors and department administrative staff (48.5%).

The syllabi and publicly available course descriptions were analyzed to determine (i) the content taught, (ii) the prerequisites or corequisites to enroll, (iii) the major the course was intended for, (iv) the academic year within the 4-year program during which students were anticipated to enroll in the course, (v) the instructors’ pedagogical approach, (vi) the grading scheme utilized, and (vi) the policies listed.

Content taught:

An iterative emergent coding method was used to develop the codes for each topic [31]. See Table IV in the Appendix A. The final coding scheme encompassed the following topics: (i) thermal physics, (ii) relativity, (iii) quantum physics, (iv) atomic physics, (v) nuclear physics, (vi) molecular physics, (vii) solid state physics, (viii) statistical physics, (ix) cosmology, (x) programming skills, (xi) mathematical foundations, (xii) history of modern physics, (xiii) particle physics, (xiv) waves, optics, lasers and/or light, (xv) astrophysics, and (xvi) Lagrangian or Hamiltonian mechanics. In order for a course to be coded as including a topic, the syllabus had to list one or more of the codes for the topics listed in Sec. IV. For example, if a syllabus stated it would cover the photoelectric effect, then the syllabus was coded as including quantum topics.

Prerequisite and corequisite requirements:

Publicly available course catalogs were utilized to determine (i) the highest level of mathematics required to enroll in the course and (ii) all physics courses required to enroll. The highest level of mathematics required to be taken prior to or during the semester of enrollment in modern physics was found in the modern physics course description from the catalogs. Courses were coded as requiring (i) no mathematics required, (ii) algebra, (iii) pre-calculus, (iv) calculus I, (v) calculus II, (vi) calculus III, and (vii) advanced mathematics. Any courses taken after

calculus III, such as linear algebra or differential equations, were considered “advanced mathematics,” as math courses are not necessarily taken in a linear sequence after the completion of the calculus series.

Physics topics required prior to enrollment were also found using the modern physics course description within the catalog. The prerequisite physics course code was recorded and then located in the course catalog. The course description was then utilized to code for each topic taught in the course. This step was necessary, as not all “Physics I” or “Physics II” courses encompass the same topics. For example, while mechanics and electricity and magnetism are most commonly referred to by the “Physics I” and “Physics II” course titles, other topics such as thermodynamics, waves, or special relativity may be included as well. The course description of the prerequisite course was used to discern this variability. The course description of the prerequisites’ course was then recorded and the course description used to code for topics taught until reaching the point where no physics prerequisites were required. This iterative process allowed for the coding of all physics topics required to enroll in the modern physics course.

Intended major of students enrolled:

The intended major of students enrolled in the modern physics course was coded to determine the audience the institution meant the course to be tailored to. Again, using the course catalogs, the physics degree requirements and sample 4-year timelines (if available) were referenced to determine if the modern physics course was intended specifically for physics majors and whether the course was a requirement for graduation.

To determine if the course was intended for majors other than physics students, the course description in the catalog was used. For example, this code would be used if the course description included a statement such as “This course is intended for students majoring in physics, philosophy, mathematics, or engineering.” If no major was listed in the description, the assumed audience was physics students, as all courses in this study were listed within the institution’s physics department.

The physics degree requirements were also referenced to determine if the course was required for a physics major to graduate. While the intended audience for many of these courses was physics majors specifically, the authors also recorded whether the courses were required for other students to receive their 4-year degree.

Year intended for enrollment:

Multiple methods were used to code for which year (i.e., freshman, sophomore, junior, and senior) students were expected to enroll in the course. Some courses included this information in the course description, in which case the course was coded using this method. If the information was not available within the description, physics degree sample timelines were referenced when available. In the event neither of these methods were available, the physics prerequisite courses were used. If there were, for example,

two required prerequisite courses to enroll in the modern physics course, it was then assumed students were expected to enroll in their third semester or sophomore year.

Pedagogical approach:

Instructors’ pedagogical approach was coded using an emergent coding method [31]. Using an iterative process, the final codes were (i) lecture based, (ii) lecture based supplemented with discussions, recitations, or in class activities, (iii) not defined, (iv) active classroom, (v) studio based, and (vi) flipped or reverse classroom. The codes for each approach are listed in Table V in the Appendix B.

Grading scheme:

The grading scheme used was coded using an emergent coding method [31]. The codes for grading were (i) skills based, (ii) curved, (iii) may be curved, (iv) may be curved but only for student benefit, (v) no curve, (vi) not stated if there will be a curve or not, (vii) pass or fail, and (viii) a rounding policy stated for use when students were on or close to a letter grade boundary. The codes for each grading scheme can be found in Table VI of the Appendix C.

A skills-based course is one in which all students could potentially receive an A in the course. The instructor does not have a quota or limit on the number of A’s that can be assigned. This grading scheme was also referred to as an absolute grading scheme. A skills-based course assigns grades based on the proficiency students demonstrate relative to the learning goals of the course.

Syllabi were also coded into three categories: (i) those that explicitly used exams as a form of assessment, (ii) those that explicitly did not use exams as a form of assessment, (iii) those that did not state whether exams were used or not as a form of assessment. The syllabi in category (i), those that explicitly used exams as a form of assessment, were further divided into three subcategories: (a) those that explicitly had one or more cumulative exams, (b) those that explicitly had noncumulative exams, and (c) those that did not state whether the exam would be cumulative or noncumulative.

Policies:

Policies were also graded using an emergent coding method [31]. The final codes can be found in Table VII of the Appendix D. The policies coded for included (i) academic integrity, (ii) Americans with Disabilities Act (ADA) accommodations, (iii) Family Educational Rights and Privacy Act (FERPA), (iv) religious observances, (v) exam policy, (vi) late or makeup work, (vii) equity, diversity and inclusion (EDI), sexual harassment, or Title IX statements, (viii) basic needs resources, (ix) attendance, (x) counseling services, (xi) regrade policy, (xii) email policy, (xiii) COVID-19, (xiv) academic success resources, (xv) campus safety, (xvi) Second Amendment, (xvii) AI or ChatGPT usage, (xviii) classroom etiquette, (xix) inclement weather, and (xx) pregnancy or childbirth.

During the initial phases of creating the emergent codebook, the authors noted two distinct cases where

policies centered on guns on campus. While the authors were originally coding all gun-related policies as a “campus safety” issue, it became clear that not all policies involving guns were centered on the safety of students on campus. There were instances where a student’s right to bear arms, based on the Second Amendment to the U.S. Constitution, was listed in the syllabi. Currently, there is no federal law restricting guns on a college or university campus [32]. Firearm regulation on campus is controlled by the state and local governments.

Focus on institutions supporting diverse student bodies:

In order to ensure the inclusion of institutions that serve the Black, Hispanic, and other diverse communities, an aggregate analysis was conducted to look at the frequency rate of topics taught at minority-serving Institutions (MSIs). The MSI types included in this aggregate analysis are historically Black colleges and universities (HBCUs, $n = 1$), Hispanic-serving institutions (HSIs, $n = 11$), Asian American and Native American Pacific Islander-serving institutions (AANAPISIs, $n = 10$), predominantly Black institutions (PBIs, $n = 1$), and Alaska Native-serving institutions or Native Hawaiian-serving Institutions (ANNHs, $n = 1$) [33].

B. Integrating human-coding and NLP methods

While the human-coding approach provided a detailed and nuanced understanding of the syllabi, it was also labor-intensive and subject to potential biases. To mitigate these limitations and enhance the robustness of our analysis, we incorporated NLP techniques. While NLP techniques are also subject to biases, by integrating the two methods, we aimed to cross-validate both methods’ results and identify additional patterns that might be overlooked by manual analysis. This complementary approach allowed for a more comprehensive and reliable examination of the syllabi data.

Furthermore, the integration of NLP and human-coding methods served a dual purpose. Not only did it enhance the analysis of modern physics syllabi, it also provided a valuable case study for testing the efficacy of NLP tools in the context of physics education research. By comparing and cross-validating the findings from both methods, we were able to assess the reliability and validity of NLP techniques in educational research settings. This approach demonstrates the potential of NLP to complement traditional human-coding methods, offering scalable and replicable tools for analyzing large datasets in PER. The novel method of this paper was conducting human coding alongside NLP for cross-validation; however, all data coding was discussed between the first and last authors as coding took place so that there was constant communication and refinement of the process.

C. Topic modeling using NLP

The analysis was framed as a *topic modeling* NLP task [17,34,35]. Topic modeling algorithms aim to learn topics

or hidden semantic patterns that exist in a corpus of text documents. They do so through a sequence of transformations. First, the documents are *tokenized* and converted to smaller units; the resulting tokens are then *vectorized*, i.e., converted to a numerical representation; the algorithm then fits the encoded documents to discover topics from the vector representation. Each of these steps can utilize a number of subalgorithms. Additionally, topic modeling algorithms generally incorporate *hyperparameters*, user selectable parameters that control the behavior of the algorithm. As part of the analysis, it is necessary to conduct a human or automated exploration of the topics identified as a function of these hyperparameters and then perform an assessment of the quality of the identified topics.

The corpus analyzed here comprised $n = 169$ documents, largely in Adobe PDF format (151 files), with 13 Microsoft Word files, 2 Microsoft Excel files, 1 HTML file, 1 plain text file, and 1 PNG file. All of these were analyzed except for the single PNG file. All files were converted to plain text for further analysis using the `pdftotext` utility for PDF files and `pandoc` for the remaining file types. As is typical with NLP methods, each plain text file was then *cleaned* by converting all capitals to lower case; removing URLs; converting newlines, punctuation, and control characters to spaces; and consolidating successive spaces.

We first attempted to apply latent Dirichlet allocation (LDA), which has previously been applied to perform a topic analysis of the Physics Education Research Conference (PERC) proceedings, to our corpus. [20,21]. Latent Dirichlet allocation assumes that each document consists of a number of topics and that each token in a document is associated with one of the document’s topics. It is necessary to remove commonly occurring words or stop words from the corpus prior to analysis. Despite exploring a wide range of hyperparameters, we did not find any satisfactorily coherent topics. In part, this is likely due to the size of the corpus which is much smaller than that explored in Refs. [20,21]. It may also be due to limitations of the algorithm. For example, the order of the tokens is not taken into account by LDA other than, optionally, as short sequences or *n-grams* of tokens. We therefore turned to a newer class of algorithms that *do* take token order into account and are pretrained on a much larger corpus.

Behind the recent explosion of LLMs is the 2017 creation of the *transformer* deep learning architecture which is able to contextualize words within their surrounding environment, providing a *context window* of a specified number of tokens. Using nonlocal information allows such models to better capture semantic structure, and the transformer architecture also facilitates parallelization for better performance. An early successful language model in this class, Bidirectional Encoder Representations from Transformers (BERT) [36], remains an important baseline model for NLP tasks. Such models are pretrained on a corpus of data, in BERT’s case English Wikipedia articles.

Here, we use the BERTopic topic modeling algorithm [37] that performs the sequence: *embedding* the corpus into a numerical representation using the BERT language model; *dimensionality reduction* into a smaller parameter space; *clustering* in the reduced space—this is the step that actually identifies the topics; and then building a *representation* of the topics. The modular design means each component can be replaced as new submodels become available. Additionally, BERTopic provides a number of hyperparameters, but there is less need for tuning than earlier techniques. Importantly, the default clustering algorithm, HDBSCAN, automatically selects the number of clusters by finding a cluster size ϵ such that changes in ϵ do not change the number of clusters generated. Our analysis sequence is similar to that used in Ref. [22], although the underlying language model used here is necessarily different due to the English texts.

In line with recommendations for usage, we modified our cleaning step to divide each text into fragments approximately corresponding to sentences using the `sent_tokenize` function in the `nlTK` package. Dividing the corpus into sentences, we obtained 11 494 fragments in total with a mean length of 69 fragments per document. In contrast with LDA, it is not recommended to remove stop words; the transformer architecture implicitly uses these words in understanding the context of other words.

IV. RESULTS

A. Results of human-coding methods

Content taught:

The results of the syllabi analysis concluded that quantum (94%), atomic (83%), and relativity (70%) were the most commonly taught topics in modern physics within the U.S., as shown in Fig. 1. Most courses also cover the historical background of modern physics (63%). Figure 2 shows the distribution of content taught at MSIs represented in the dataset. Within the MSIs, quantum was always taught (100%), atomic was taught less often than seen in the larger dataset (73%), and relativity was taught slightly more often than seen in the larger dataset (73%).

Prerequisite and corequisite requirements:

The analysis of the course descriptions concluded that the majority of students enrolled in modern physics had already taken calculus II (89.3%) or higher, as shown in Fig. 3. As for physics backgrounds, students most commonly had previously been enrolled in courses that had introduced students to Newtonian physics (94%), electricity and magnetism (84.4%), and waves/optics (77.2%). See Fig. 4.

Intended major and year of students enrolled:

Of the institutions, 74% expected students to enroll in modern physics during their second year (Fig. 5). It should be noted that the 4% of the institutions targeting modern

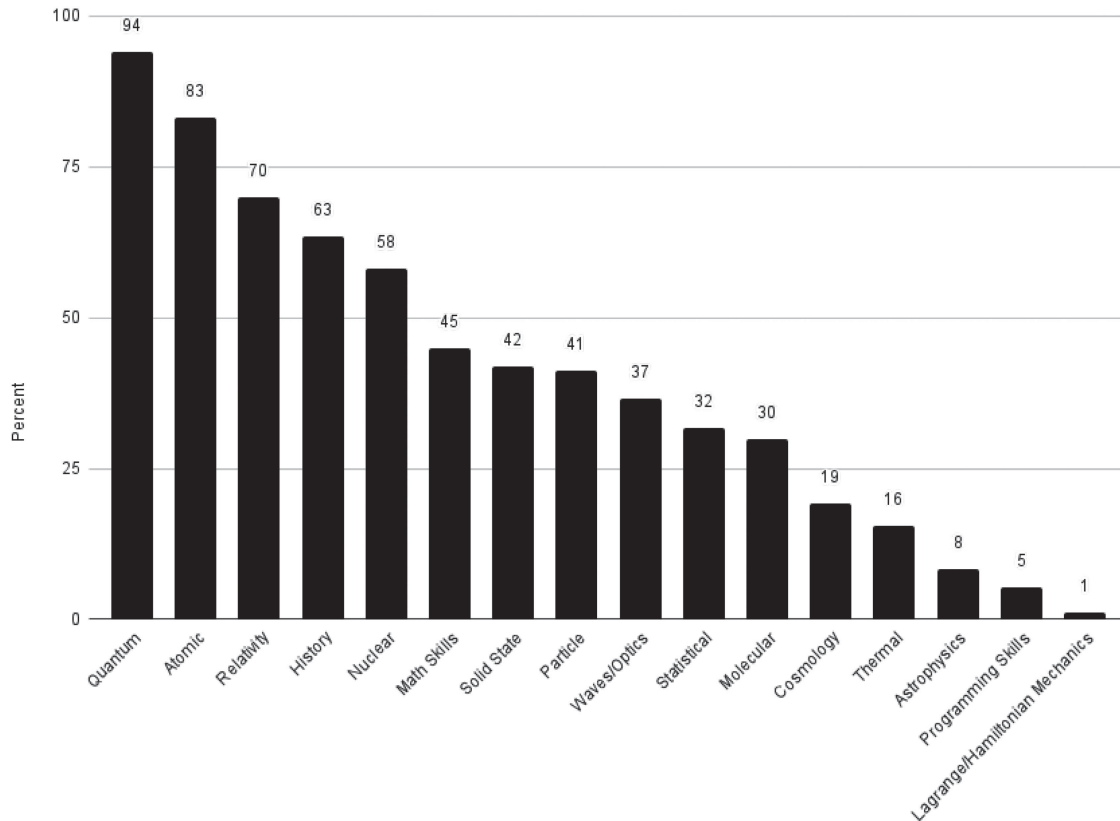


FIG. 1. Topics taught in 167 modern physics courses across the U.S.

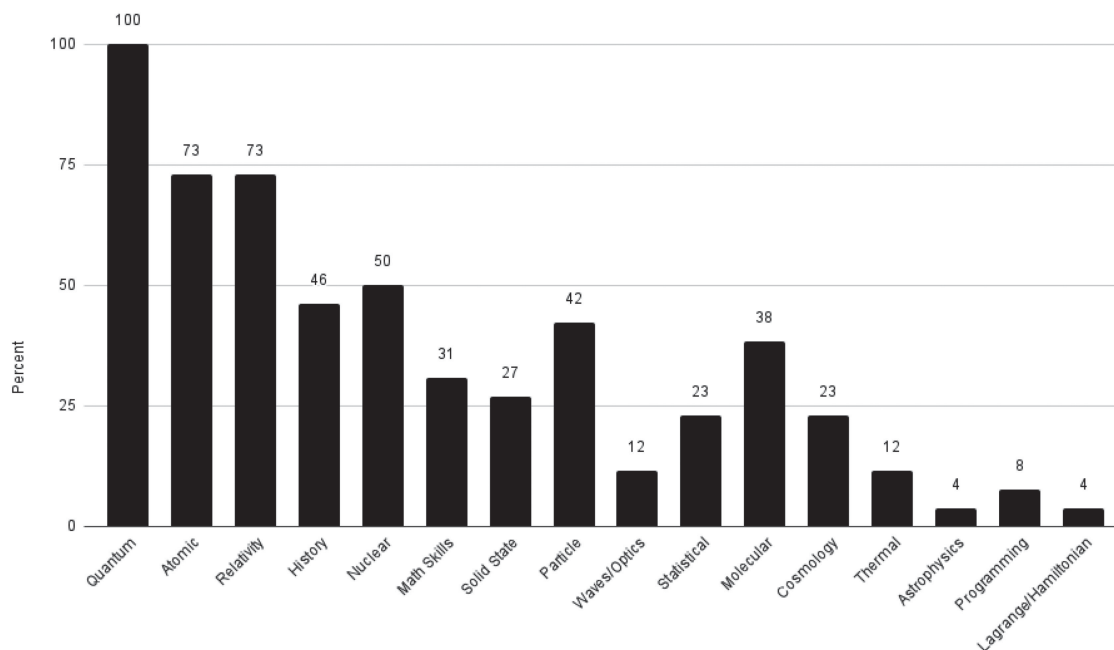


FIG. 2. Topics taught in modern physics courses at MSIs.

physics courses for fourth-year students were teaching traditional quantum mechanics courses but titled their course as modern physics, making them an outlier in the dataset. These courses, however, were not removed from the dataset, as the motivation for this paper was to determine what “modern physics” means to different institutions across the U.S. In order to encompass the full

range of definitions of the modern physics course, any course title containing “modern physics” was included despite its definition being in contrast to the rest of the dataset. It can also be noted that the modern physics courses that more closely resembled a quantum mechanics course were the courses that added topics such as Fermi’s Golden Rule to our emergent coding listed in the Appendix A.

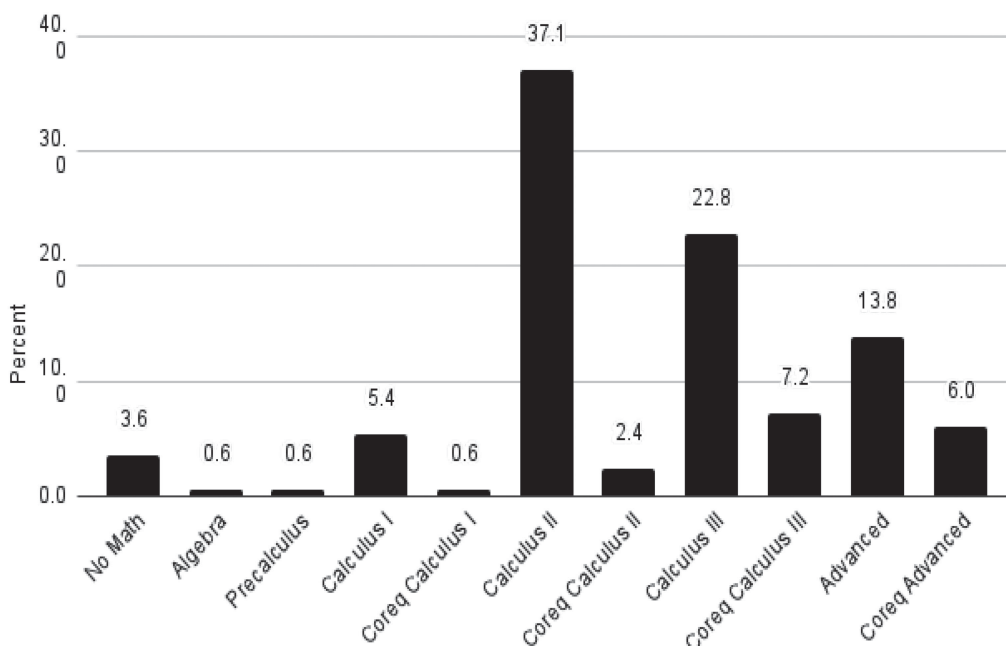


FIG. 3. Mathematics prerequisites and corequisites.

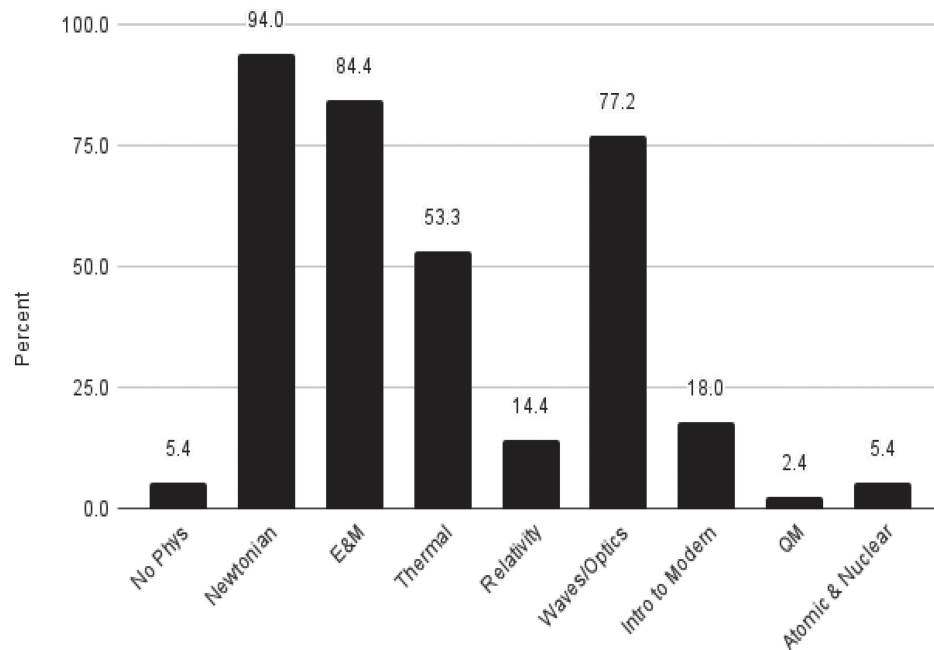


FIG. 4. Required physics topics taught prior to enrollment in modern physics.

While 92.2% of courses were intended for physics majors, only 70.7% of those were explicitly required for physics majors to graduate (Fig. 6).

Pedagogical approach and grading scheme:

Of the 167 syllabi, $n = 36$ (21.6%) did not define a pedagogical approach (Fig. 7). Furthermore, $n = 125$ (74.9%) were lecture based, with $n = 79$ (47.3%) having additional discussions, activities, or participation components built into the lecture or designated for a different time. Additionally, $n = 6$ (3.6%) used an active classroom format, $n = 4$ (2.4%) used a studio style, and $n = 2$ (1.2%) used a flipped classroom approach. Some courses that used active, studio, or flipped classroom approaches also had designated lecture times built in and were included in the $n = 125$ (74.9%) of lecture-based courses.

Whether instructors would be curving student grades in the course was ambiguous. Of syllabi, 78% did not state whether there would or would not be a curve (Fig. 8).

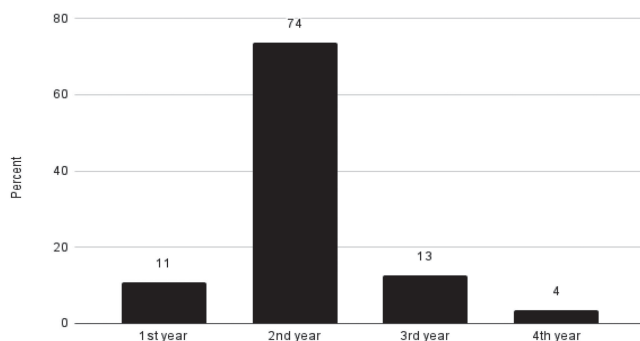


FIG. 5. Intended year of enrollment.

About 7% stated there would be no curve, while 6% stated the grade would curve only for the students' benefit. About 4% stated there may be a curve without indicating if student grades would increase or decrease as a result of said curve. About 5% explicitly stated there would be a curve but did not state that students would necessarily benefit from it. From the literature [14], it is known that in STEM classrooms, the use of curves creates a "chilly climate" that is particularly harmful to women and underrepresented students. Curves create unnecessary competition between students, especially when collaboration and discussion between students are known to benefit student learning. By more distinctly outlining the policy on curving in the syllabus, instructors would be setting the precedent for a more collaborative and inclusive course environment prior to the start of the course.

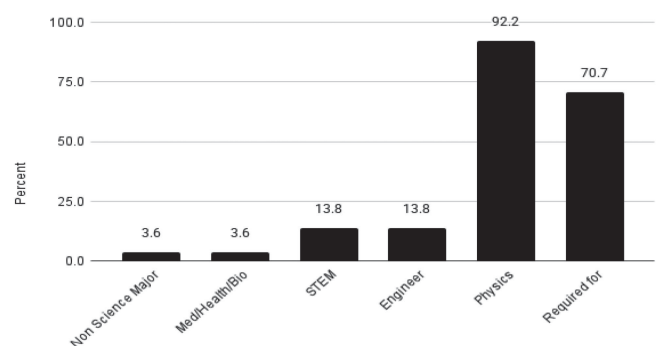


FIG. 6. Intended audience of the course and if intended for physics majors, if it is required for physics majors to graduate.

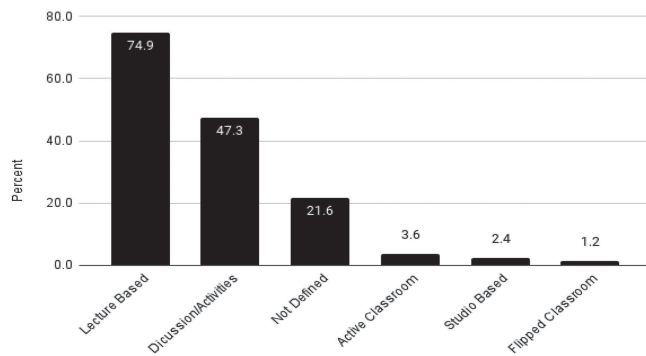


FIG. 7. Pedagogical approach utilized.

About 3% explicitly used a skills-based, or an absolute scale, stating all students could hypothetically receive an A, 6% of syllabi had a policy on what grade would result if a student's grade was on a letter grade boundary, and 2% of courses were using a pass or fail grading system.

Of the 167 syllabi, 3% explicitly state exams would not be used as an assessment tool, 7% of the syllabi did not state whether there were or were not exams, while 90% explicitly stated there would be exams (Fig. 9). Of the 90% of syllabi with exams, 50% had a cumulative exam, 10% had only noncumulative exams, and 40% did not state whether exams would be cumulative or not (Fig. 10).

Policies:

At least one policy was listed in 83.2% ($n = 139$) of the syllabi. The most common policy, seen in 78% of the 139 syllabi, concerned late or makeup work. As shown in Fig. 11, 76% had a statement on academic integrity and 69% had a policy or university policy listed as Americans with Disabilities Act (ADA) or other accommodations.

B. Results of topic modeling using NLP

Topic modeling using NLP:

Running BERTopic on the same corpus 20 times produced between 97 and 105 topics due to the stochastic nature of the underlying algorithm. For each topic, the algorithm provided the ten words most associated with the topic and a measure of their relative weight. For processing,

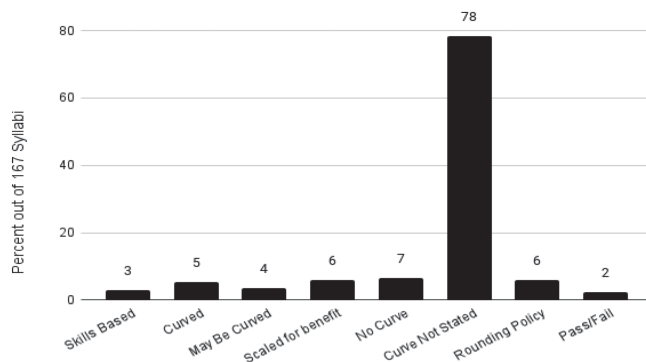


FIG. 8. Grading scheme utilized.

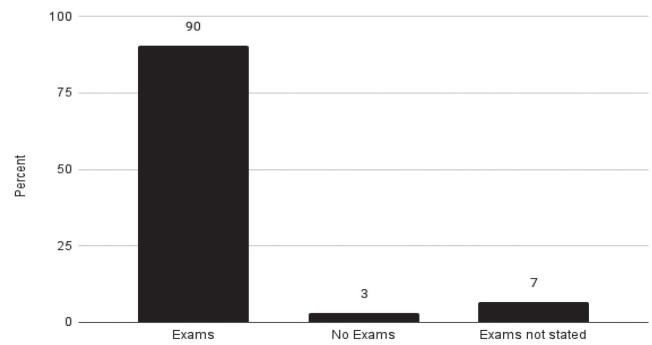


FIG. 9. Use of exams as assessment tool in modern physics courses.

each document is divided into sentence fragments, the classified groups then recognize and assign one topic per sentence fragment. Since it is known which document the sentence fragment came from, we mapped the sentence fragments back to their parent syllabi to compute the frequency with which each topic occurred in the original corpus. In Table I, we show the ten topics that appeared most frequently in the syllabi from a typical run with BERTopic—these were robust across runs—together with the ten words most associated with each topic. We also provide a prototypical example sentence, automatically generated by the algorithm, close to the center of the topic cluster. Finally, we also provide a brief researcher-generated interpretation of the topic.

Most topics identified concerned the expected content of syllabi including various components and policies. The sixth topic in Table I, for example, concerns exams, and occurred in 91/169 documents, a number that almost exactly matches with the human-coded results in Fig. 9. Importantly, however, the NLP algorithm was *not* able to resolve the small number of examples of a “no exam” policy, likely because these were very rare in the dataset.

Not all topics generated were useful for our analysis. The second topic for which we did not provide a prototypical sentence appears to correspond to common words appearing in syllabi. Such topics that appeared to neither involve policy nor content were assigned to a “not used” category.

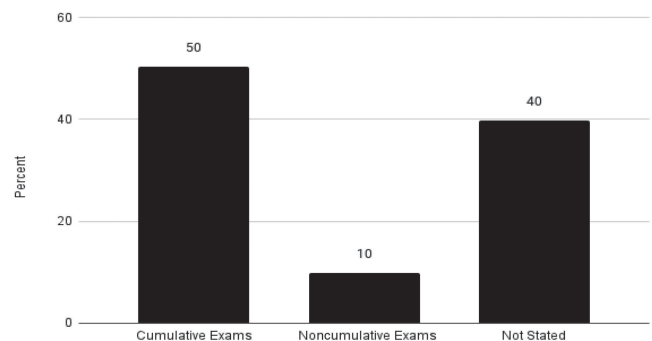


FIG. 10. Use of cumulative and noncumulative exams.

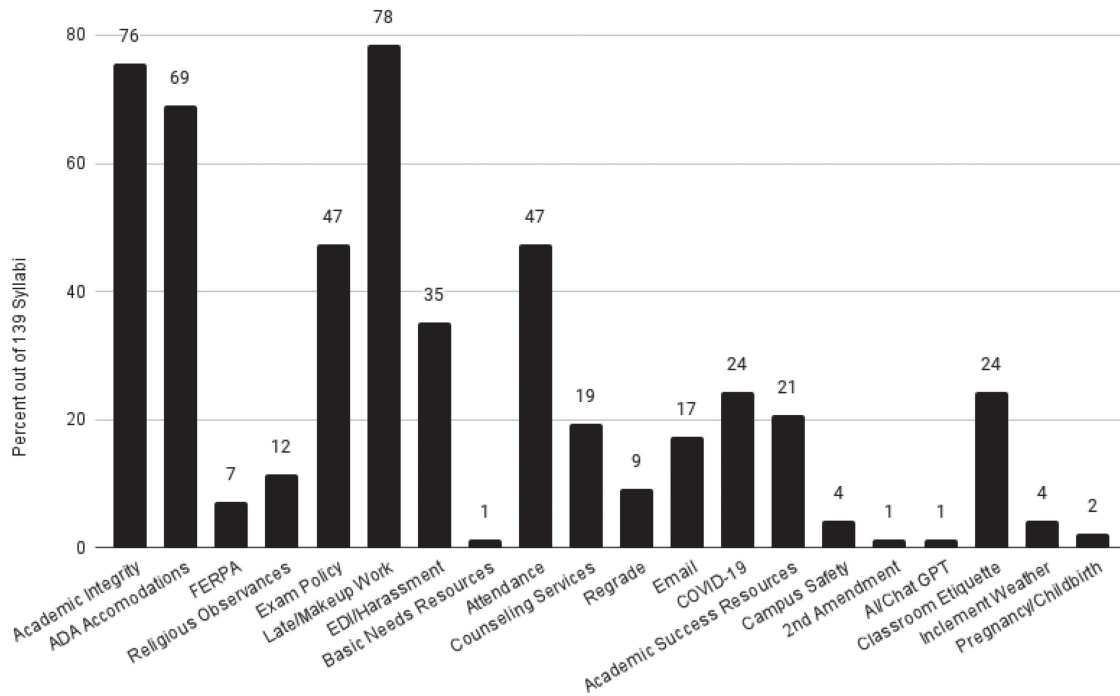


FIG. 11. Policies listed in modern physics syllabi.

The remainder of the topics were divided into “policy” and “content” topics and used to cross-validate our human-coding process.

We began by comparing the emergent topics from the NLP analysis to the policies identified in Fig. 12. For each human-coded topic, we identified similar NLP topics by looking for similar words. The results of this analysis are displayed in Fig. 12 which places the frequency distributions for human codes alongside those computed for the largest closely related topic identified by the BERTopic algorithm. The relative frequencies are strikingly similar for many topics, providing substantial evidence that validates the codes chosen and the coding procedure used.

In some cases, the NLP algorithm identified more than one topic that appeared to be related to the human code. For example, the human code “academic integrity” appears to be related to the four topics displayed in Table II. The topics identified by NLP may nonetheless capture different aspects of academic integrity. The first aspect may be associated with academic misconduct and violations or consequences; whereas, the last seems to be associated with honor codes. Researchers encountering a similar phenomenon could choose a number of approaches. They might choose to further investigate the differences between topics, either through human reading or by computing similarity scores; or, they may choose to collapse selected topics. Here we collapsed all topics associated with a human code into a single topic and used the size of the combined topic for the frequency count.

As for the simple example on exam policies presented earlier, topics that were identified through human coding

that were rare in the dataset were not resolved by the NLP algorithm. No topics were identified by BERTopic that are related to any of the Family Rights and Education Privacy Act (FERPA), basic needs assistance, regrading policy, the Second Amendment, AI or ChatGPT (the researchers noted this omission with amusement), or pregnancy and childbirth codes. These elements are certainly in the text but were seen too infrequently to survive the clustering process. Some of these topics, such as pregnancy and childbirth, were closely related to issues of equity, and hence we observed an important possible source of bias if NLP analysis were to be relied on exclusively.

The NLP analysis *did* identify some policy topics that appeared to be distinct from those chosen in the human-coding process. We display these in Table III, together with a brief researcher-generated interpretation. A third of the syllabi mentioned policies related to athletics or extracurricular activities which were not coded for in the human analysis. The human analysis did not include these policies, and instead, any statements related to athletics or extracurricular activities were grouped into the more broad policy category of absences. While athletics and extracurricular activities are distinctly different from other absences, the human analysis missed this nuance and grouped the two together. Other topics are arguably related to human-coded topics: incomplete grades and withdrawals are related to grading policies overall, and copyright and citations are related to academic integrity. Nonetheless, it is interesting to note that some syllabi explicitly mentioned these topics. While we did not do so here, NLP-generated topics could serve as a basis for a follow-up analysis.

TABLE I. Ten most frequent topics identified by BERT_{topic}, showing for each topic: its frequency in the corpus of syllabi, the top ten words associated with the topic, a prototypical sentence, and a brief researcher-generated interpretation.

Frequency	Ten most relevant words	Prototypical sentence fragment	Interpretation
121 (73%)	grading, grades, grade, graded, grader, exam, assignment, scores, quizzes, calculated	“grading policy grade components your semester average will be determined as follows...”	How grades are calculated
120 (72%)	syllabus, instructor, lecturer, edu, prof, professor, college, prerequisites, curriculum, astronomy	...	Common words that appear in syllabi
100 (60%)	disabilities, disability, disability services, accommodations, accessibility, accommodation, rehabilitation, handicapped, eligibility, eligible	“Americans with disabilities act students with disabilities needing academic accommodations should...”	Academic accommodations
97 (58%)	textbooks, textbook, books, fundamentals, texts, isbns, library, ebook, book, isbn	“required and recommended materials text book any calc based text with modern physics physics for scientists and engineers...”	Suggested textbooks
94 (58%)	lectures, lecture, study, textbooks, textbook, reading, texts, readings, courseworks, notes	“be diligent about the reading assignments be on time to class and turn in your completed homework when you arrive”	Lecture component
91 (55%)	exams, exam, examinations, examination, midterm, midterms, quizzes, schedule, final, testing	“the midterm exams will be held in rooms to be announced in class and will take place during the scheduled quiz time see above”	Exam policies
85 (51%)	homeworks, tutors, lateness, tutoring, deadline, homework, late, credit, overdue, penalized	“late homeworks will be accepted with a credit penalty through Friday at the beginning of the class”	Homework policies
71 (43%)	calculators, calculator, calculate, formulas, calculations, equations, calculation, numerical, numerically, formulae	“calculators are allowed and a formula sheet together with physical constants can be used”	Policy on use of calculators
67 (40%)	misconduct, disciplinary, sanction, integrity, expulsion, consequences, violates, student, violations, academic	“academic misconduct is a violation of the [redacted] student code of conduct subject to a maximum sanction of disciplinary suspension or expulsion as well as a grade penalty in the course”	Academic misconduct policies
66 (39%)	instruction, lecturers, learning, scholarship, pursuing, literacy, learn, struggling, design, barriers	“there are many ways to get help in this course and we hope you do contact any member of the instructional team if you feel unsure about the material and worry about your grade”	Support mechanisms

We identified 15 emergent topics that corresponded to course content as shown in Fig. 13. By comparing these with codes used for the manual coding process, each NLP-generated content topic was assigned to a human-coded

topic. Only one topic, which occurred in 21 documents, was not assigned and was associated with the words “circuits, electrodynamics, electromagnetism, electromagnetic, conductors, faraday, electricity, electric, electrostatics, currents.”

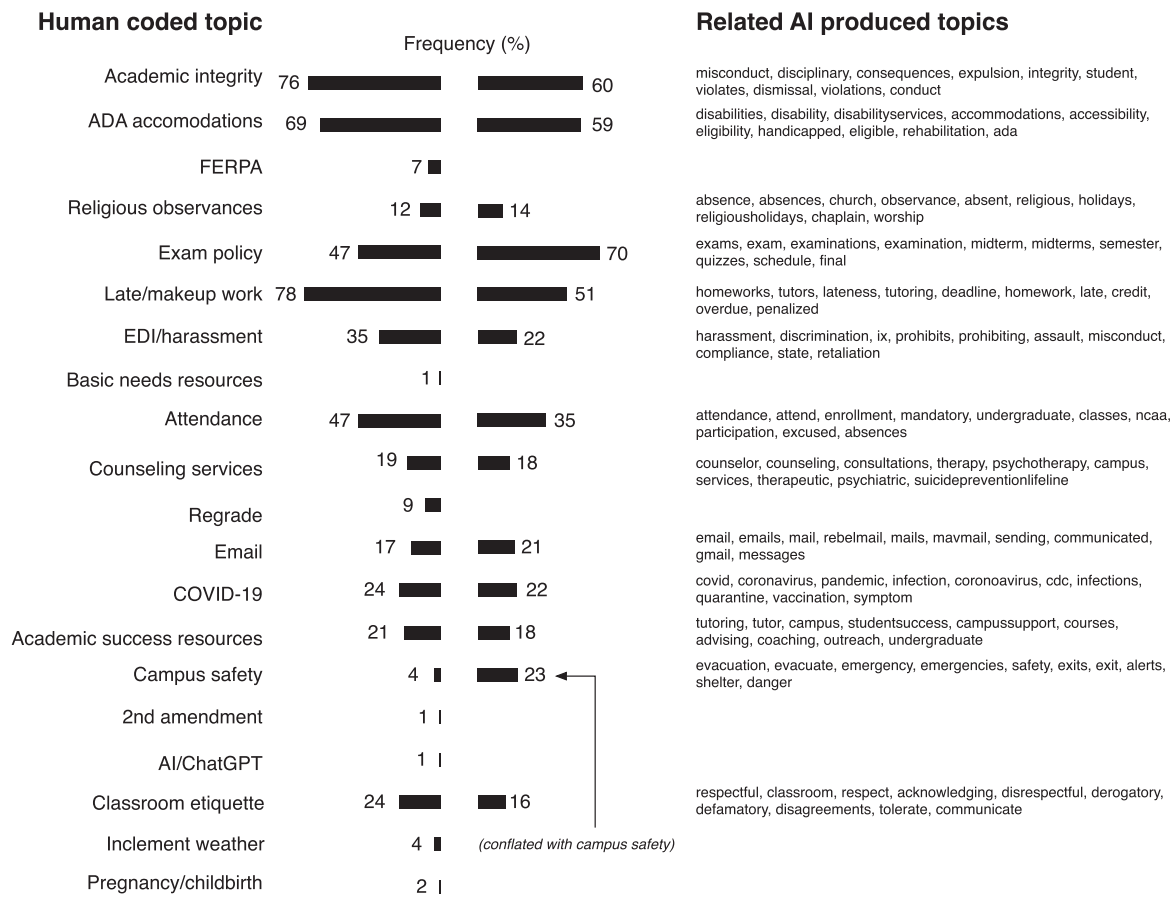


FIG. 12. Comparison of policy topics identified by human coding (left) and NLP BERTopic coding with associated words (right).

TABLE II. BERTopic-generated topics associated with the human-coded topic “academic integrity”.

Frequency	Ten most relevant words	Prototypical sentence fragment
70 (41%)	misconduct, disciplinary, consequences, expulsion, integrity, student, violates, dismissal, violations, conduct	students must recognize that failure to follow the rules and guidelines established in the university's code of student conduct and this syllabus may constitute academic misconduct...
40 (24%)	integrity, academic integrity, scholarly, academic, scholars, institution, scholarship, faculty, trust, excellence	as described in the [Redacted] academic integrity is the basic guiding principle for all academic activity [Redacted] allowing the pursuit of scholarly activity in an open honest and responsible manner
27 (16%)	integrity, academic, honesty, ethics, ethical, education, scholarly, academichonesty, informational	academic honesty [Redacted] has a comprehensive academic honesty policy document a culture of honesty which is available from office of the vice president for instruction at...
26 (15%)	honor, integrity, pledge, academic, university, upholding, studenthealth, academics, uphold, acceptance	the honor code reads as follows to promote a stronger sense of mutual responsibility respect trust and fairness among all members of the [Redacted] community and with the desire for greater academic and personal achievement...

TABLE III. Topics identified by BERTopic that are distinct from those identified by human coding.

Frequency	Ten most relevant words	Prototypical sentence fragment	Interpretation
59 (35%)	extracurricular, curricular, activities, intercollegiate, athletics, athletic, excused, activity, competitions, accrued	for purposes of definition extracurricular activities may include but are not limited to academic recruitment activities competitive intercollegiate athletics fine arts activities liberal arts competitions science and engineering competitions and any other event...	Extracurricular and athletic activities
33 (20%)	incompletes, incomplete, grade, semesters, gpa, deadline, certifiable, nullified, requirements, absence	incompletes you may be assigned an incomplete for the course in accordance with the [Redacted] regulations provided all of the following applies you received a non failing grade in labs you received a non failing grade on at least one exam no violation of the academic honesty policy took place during the course of the semester	Incomplete grades
22 (13%)	withdrawn, withdrawing, withdrawal, withdraw, [Redacted], withdrawals, [Redacted], [Redacted], deadline, deadlines	for medical withdrawals requests to college to be dropped from a class after the deadline for withdraw has passed the withdraw pass wp or withdraw fail wf grade will usually be determined by the pro rated grade...	Withdrawals
17 (10%)	copyright, copyrighted, infringement, copying, license, documents, infringe, copied, violates, prohibited	copying displaying reproducing or distributing copyrighted works may infringe the copyright owner's rights and such infringement is subject to appropriate disciplinary action as well as criminal penalties provided by federal law	Copyright
12 (7%)	citations, citing, bibliography, cite, citation, cited, references, researching, wikipedia, guides	citation is commonly done use a style manual which provides guidance on how to format the information for a citation such as title author pages and date as well as formatting and grammar specifics	Citations

As can be seen in Fig. 13, while many of the content topics were also identified by the NLP analysis, the frequency estimates are considerably poorer than those from the policy analysis. This is likely due to the language model used by BERTopic that may not properly capture physics and math terminology.

C. Results of human coding for cross-validation of NLP analysis case study

As stated previously, field testing the NLP methods with low risk datasets such as this one is important for validating the use of the NLP method with PER. In order to field-test the NLP method with this dataset, a code that the NLP method *found* and the human-coding method *did not find* was selected and then coded by the human for cross-validation.

The NLP method found 35% of the syllabi included policies related to extracurricular activities and athletic activities. Using a human-coding analysis, it was found that 18% of syllabi had policies related to extracurricular and athletic activities. However, this discrepancy in frequency is most likely due to the human-coding method only counting this policy for instances of “athletics,” “extracurricular activities,” “university business”, or events in which the “student is a representative of the institution,” whereas the NLP included the word “excused” in this code. The term “excused” can be applied to a much broader range of reasons for an absence than a university event or activity. In the previous section, the human-coding analysis had coded for any absentee policies in the syllabi and found that 40% of syllabi had such a policy. However, these absentee policies may not have included the word “excused” in

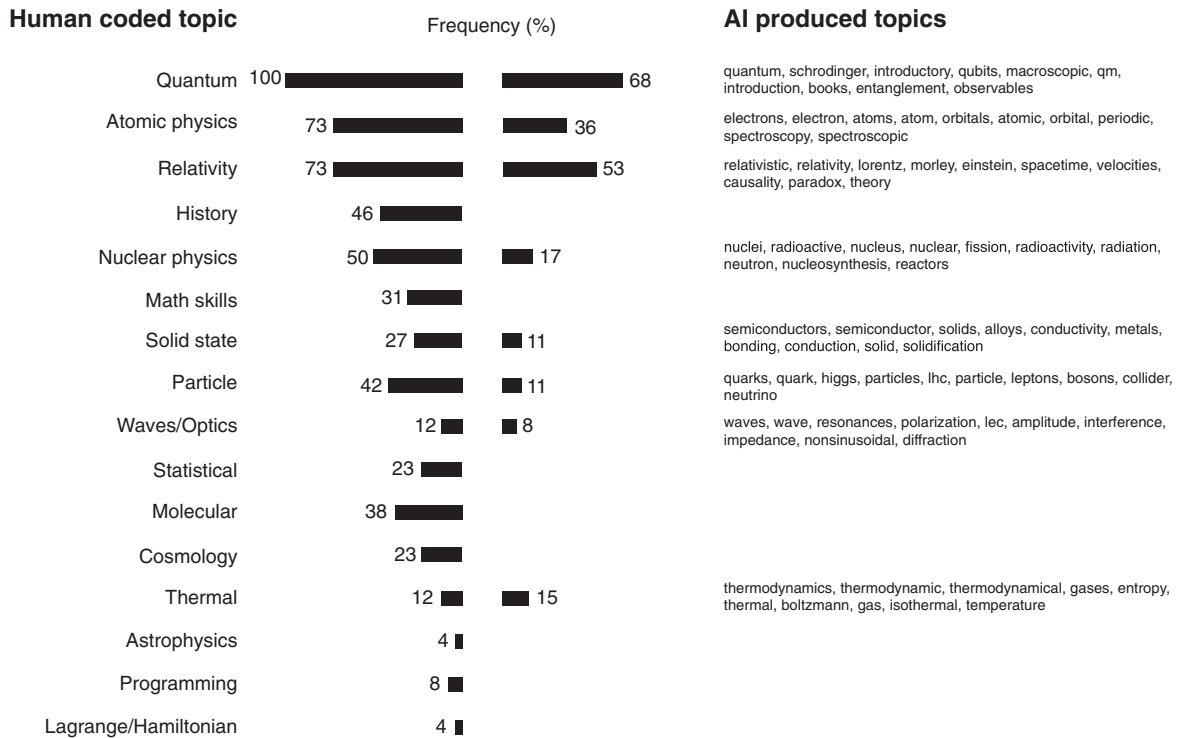


FIG. 13. Comparison of content topics identified by human coding (left) and NLP BERTopic coding with associated words (right).

them, which may be why this frequency count is higher than that seen in the NLP absence policy count.

V. DISCUSSION

With quantum being the most commonly frequently introduced topic, and 70.7% of modern physics courses intended for physics students being a graduation requirement, it can be concluded that modern physics is the students' first introduction to concepts within quantum mechanics. This conclusion echoes the speculation made by Vokos *et al.* [5] and Singh *et al.* [3]. However, because the majority of students enrolled in modern physics have not yet seen linear algebra or differential equations, the modern physics course must only be an introduction to quantum mechanics. Without an understanding of the more advanced mathematics courses, students are not yet ready to tackle problems in commonly used undergraduate textbooks such as Griffiths [38] or McIntyre [39]. Therefore, in order for students to solve quantum mechanics problems at the level of Griffiths or McIntyre, they will need another course on quantum mechanics later in their undergraduate career. Without having seen linear algebra prior to enrollment in modern physics courses, it would be interesting to determine if any of these courses are using a spins-first approach to quantum concepts.

Physics educators may want to teach students more about quantum mechanics earlier on in their undergraduate career, but the reality is that the majority of students come to university underprepared. Fewer than one in four

American 12th graders performed proficiently in math on the National Assessment of Educational Progress in 2019 [40]. The uniqueness of individual institutions' student bodies must be considered when designing a program and determining the level of introduction to quantum that students are ready for, particularly regarding math preparedness.

It can also be drawn from these results that research-intensive programs have converged on the inclusion of quantum concepts, atomic physics, and relativity within their modern physics courses, without having a community conversation or consensus. An analysis of syllabi from modern physics courses taught at smaller, teaching-focused institutions could reveal interesting results regarding whether they have converged on the same set of topics as the research-intensive institutions. If the topics were discovered to be different, this could be the start of a community conversation or consensus to increase equal access to education, regardless of the institution type.

Introductory physics courses, such as Classical Mechanics and Electricity and Magnetism, have undergone significant changes to increase the level of interactivity and decrease the amount of lecturing. While syllabi are a limited and inconclusive source of information on the pedagogical approach used in the course, *the results of this study suggest that the level of interactivity within introductory courses to modern physics has decreased.* Future research efforts may aim to better understand the usage of pedagogical innovation in the modern physics classroom. *With modern physics being a*

gateway course for the physics major, physics educators should strive for this course to be inviting. Educators could potentially experiment with different pedagogical approaches and grading schema apart from the traditional approaches. The level of programming opportunities mentioned within the syllabi was low (5%). This could be another opportunity for introduction to computation, an important topic for students pursuing a career in physics or research.

In this study, the NLP task of topic modeling was performed as a methodology for cross-validation of a human-centered coding process. This was possible because the tractable size of the authors' corpus allowed for human analysis. This methodology offers valuable insight into the promise, potential applications, and limitations of NLP methods in qualitative work. With modest effort on the part of the researcher, NLP methods provided a broad perspective of the content of the corpus. Like others [22], we found that transformer-based algorithms generated more immediately interpretable results than earlier methods, with little need for the tuning of hyperparameters.

In the present case, most of the human identified codes were also separately identified by the BERTopic algorithm, suggesting that generated topics are a good starting point for qualitative analysis, at least for the kind of curricular data discussed here. By design, to facilitate validation, we conducted the NLP analysis entirely separately from the human coding process. Nonetheless, we concur with others [20–22] that such analyses can be synergistic and believe that the iteration of human and NLP analysis would be beneficial in other contexts.

A particular focus for human intervention is that the NLP analysis does not capture *rare* but potentially interesting features of the dataset. In this sample, for example, the NLP analysis was not able to capture the fact that 2% of the syllabi referred to pregnancy, 1% referred to AI or ChatGPT, and 3% referred to Lagrangian or Hamiltonian

mechanics. Neglecting the uncommon has important implications for equity. Further, the frequencies with which topics were identified showed similar overall trends between both methods. We noticed a broad tendency of the NLP algorithm to *undercount* topics, particularly for the topics associated with the course content. The undercounting may reflect biases of the training set of the BERT embedding used; language models specifically trained on physics and math texts may therefore considerably enhance the accuracy of the results. While not used here, LLMs that utilize larger models may also add utility, particularly because LLMs could be used to generate descriptions of clusters from the corpus, which may further improve the interpretability of topics.

VI. CONCLUSION

Quantum concepts are most commonly first introduced to students in their modern physics courses, making the course a pivotal experience for the physics major. With most students only having completed calculus II at the time of enrollment, students will require another course on quantum mechanics in order to be able to solve the Schrödinger equation on their own. The modern physics course also opens opportunities for institutions to work together to lessen disparities in educational access regardless of institution type, ensuring that all students are offered a comprehensive education. Additionally, there is an opportunity for instructors to implement more interactive pedagogical approaches and innovative grading schemes, rather than falling back on the traditional approaches. NLP as a methodology for cross-validation of human-centered coding has shown promise, as the two methods were often in agreement; however, the human-centered coding revealed rare or interesting cases that the NLP missed, and the NLP analysis did identify aspects that appear to be distinct or nuanced from those chosen in the human-coding process.

APPENDIX A: CODES FOR CONTENT TAUGHT

TABLE IV. Codes for content taught.

Content codes		
Thermal	Relativity	Quantum
Thermal equilibrium	Special relativity	Schrödinger
Entropy	General relativity	Schrödinger equation
Heat	Spacetime	Photoelectric effect
p-V diagrams	Invariants	Wave-particle duality
Ideal gas law	Frame transforms	Operators
Kinetic theory	Lorentz	Eigenvalues/vectors
Pressure	4-vector	Tunneling/reflection
Temperature	Metric tensor	Stern-Gerlach experiment

(Table continued)

TABLE IV. (Continued)

Content codes		
Thermal	Relativity	Quantum
Temperature	Minkowski	Dirac notation
Heat capacity	Michelson-Morley experiment	States
Specific heat	Time dilation	Quantum measurement
Carnot cycle	Length contraction	Expectation value
Bernoulli's equation	Energy-momentum	Uncertainty
Pascal's principle	Classical relativity	Superposition
Archimedes' principle	Einstein's postulates	Mixed states
	Twin paradox	Quantization
	Relativistic dynamics	Fermi's golden rule
	Relativistic energy	Photons
	Relativistic momentum	Pauli's exclusion principle
	Mass-energy equivalence	Square well
		Identical particles
		Matter waves
		Frank Hertz experiment
		Wave mechanics
		Wave functions
		Wave properties of particles
		Particle properties of waves
		de Broglie hypothesis
		Quantum theory of light
		Blackbody radiation
		Planck's postulate
Atomic	Nuclear	Molecular
Atomic	Nucleus	Molecules
Atom	Nuclear Atom	Bonds
Bohr model	Fission	Molecular spectroscopy
Thomson/plum pudding model	Fusion	Quantum theory of molecules
Rutherford model/experiment	Decay	Chemical bonding
Zeeman effect	Radioactivity	Vibrational and rotational energies of molecules
Hydrogen	Strong interaction	
Many electron atoms	Weak interaction	
Spectra	Alpha decay	
Emission/absorption	Beta decay	
Periodic table	Gamma decay	
Scanning tunneling microscopy	Nuclear force	
	Electron capture	
Solid State	Statistical	Cosmology
Solids	Bose-Einstein	Chronology of universe
Semiconductor	Fermi-Dirac	Big bang theory
Superconductivity	Quantum statistics	Evolution of universe
Band structure	Classical statistics	Structure of universe
pn-junction	Maxwell-Boltzmann	Cosmic microwave background
Condensed matter	Classical gas	
Crystal structure	Quantum gas	
Programming skills	Math skills	History
Numerical investigation	Operators	Michelson-Morley experiment
<i>Mathematica</i>	Eigenvalues/vectors	Photoelectric effect

(Table continued)

TABLE IV. (*Continued*)

Igor Pro	Dirac notation	Stern-Gerlach experiment
Python	Simple harmonic oscillator	Frank Hertz experiment
Numerical project	Simple harmonic motion	Compton effect/scattering
Computational project	Fourier analysis	Bohr model
	Matrices	Thomson model
	Complex algebra	Rutherford model
	Hilbert space	Milikan oil drop experiment
	Mathematical description of waves	de Broglie hypothesis
	Normalization	Einstein's postulates
	Complex notation	Blackbody radiation
	probability	Double slit experiment
	Expectation value	Classical vs quantum measurement
	Spherical coordinates	Planck's postulate
	Radial equation	Michelson interferometer
	Math review	Origins of quantum mechanics
	Symmetries	Early quantum theory
		Higgs boson
		birth of quantum mechanics
		Quantum paradoxes
Particle	Waves/optics	Astrophysics
Standard model	Electromagnetic waves	Stars
Fundamental interactions	Resonance	Celestial bodies
Quark model	Oscillations	Newtonian gravitation
Bosons	Interference	Kepler's laws
Fermions	Diffraction	Orbits
Neutrinos	Sound	Spectroscopy in astronomy
Higgs boson	Doppler effect	
	Reflection	
	Snell's law	
	Mirrors	
	Lenses	
	Polarization	
	Classical waves	
Lagrangian/Hamiltonian mechanics	Other uncoded topics	
	Quantized electromagnetic fields	
	Quantum electrodynamics	
	Quantum chromodynamics	
	Quantum field theory	

APPENDIX B: CODES FOR PEDAGOGY USED

TABLE V. Codes for pedagogy used.

Pedagogy codes		
Lecture based	Activities accompanying lectures	Studio based
Any instance of the word lecture occurring	Discussions/activities/recitations/tutorials supplementing lecture based class Clicker questions in lecture In class assignments	Any instance of the word "studio"

(*Table continued*)

TABLE V. (*Continued*)

Pedagogy codes		
Lecture based	Activities accompanying lectures	Studio based
	Students present solutions to class Class participation in lecture required	
Active classroom	Reverse classroom	Not defined
Any instance of the word “active” to describe classroom environment Uses lecture/ class time exclusively for discussions or activities	Any instance of the word “reversed” or “flipped” to describe classroom	Pedagogy not stated, requirements for other pedagogy codes not met

APPENDIX C: CODES FOR GRADING SCHEME USED

TABLE VI. Codes for grading scheme used.

Grading scheme codes		
Skills based	Curved	Curve not stated
Everyone can get an A Students not in competition No desired bell curve or grade distribution	Explicitly states there will be a curve Letter grade for percentage score not determined till course complete Sliding scale that does not specify if it will benefit students or not A tentative scale is given	No clear statement whether grade will be curved or not
May be curved	No curving	Scaled only for students benefit
Curve may or may not be applied depending on distribution Nothing explicitly stating if this curve will benefit or hurt students grades	Explicitly states course will not be curved (but did not state everyone can get an A) Absolute scale used	Curve/scale explicitly stated will only increase students grades
Rounding policy	Pass/fail	
States how students grades will be rounded if on letter grade boundary		

APPENDIX D: CODES FOR POLICIES LISTED

TABLE VII. Codes for policies included.

Policy codes		
Are policies included? Codes for if any policy was listed	Academic integrity Any statement about cheating, plagiarism, or honor code	Disabilities/accommodations Americans with Disabilities Act Accommodations
FERPA	Religious observances	Exam policies

(Table continued)

TABLE VII. (Continued)

Policy codes		
Any statement about FERPA or student privacy or records		Materials allowed on exams
Policy on recording lectures		
Late/makeup work	EDI or harassment	Basic needs resources
Exam makeups	Title IX statement	Food
Extensions	Sexual harassment statement	Shelter
	EDI statement	Sleep
		Nutrition
Attendance	Counseling services	Regrade policies
Is there an attendance policy listed?	Intuition counseling center or mental health services listed	How regrades will be handled and timeline allocated to request a regrade
Email policy	COVID-19 policy	Academic success resources
How professor prefers to be contacted	Mask policy	Time management coaches
How to email professor	COVID reporting policy	Writing centers
		Tutors
Campus Safety	Second Amendment	AI/ChatGPT
Evacuation plans	Open carry policies	
Class etiquette	Weather	Pregnancy/childbirth
Classroom expectations on behavior	Statement on cases of inclement weather	
Cell phone, laptop, or electronics usage in class		
Civility statement		

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