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Using Embeddings to Uncover the Similarity Between Engineering Education Doctoral Programs and Academic Workforce Opportunities

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Introduction and Background

This is a full methods paper. Artificial intelligence (AI) has recently emerged as a powerful tool to conduct sophisticated analyses on different types of data. In education research, there has been a call for novel research that utilizes generative AI to demonstrate its efficacy and accuracy [1, p. 29]. Additionally, generative AI holds significant potential in the field of engineering education, particularly in research. The community has urged scholars to document best practices for its application and present case studies to demonstrate its effectiveness [2].

Embeddings and cosine similarities are two approaches that leverage AI to evaluate qualitative data. Embedding models take raw real-world objects as inputs and generate embeddings, which are vector representations of those objects in a high-dimensional space. Embeddings encode some notion of similarity between objects. Two similar objects will have embeddings that are close together in high-dimensional space. Anchoring on similarity makes embeddings applicable as inputs to large language models and enables evaluation of similarity between text, images, etc. Quantifying an otherwise typically qualitative process allows for faster and more automated analysis [3]. Sentence embedding models take in a sentence or paragraph as input and generate a single embedding as output [3].

We use an embedding similarity technique in an application of Engineering Education (EngE) research. EngE emerged as a research field in the early 2000s, a notable shift away from a sole pedagogical focus [4]. Around the same time, newly formed engineering discipline-based academic units began offering PhDs and other graduate degrees in EngE to prepare students for future faculty careers [5]. These programs recognized that candidates qualified in engineering who could also bring expertise in pedagogy and assessment would be especially desirable for academic jobs [5]. In the years following, scholars came together to establish the boundaries of the discipline [6], [7]. However, since its inception, consensus around priorities in EngE has been weak, plagued by its originating tension between the relative importance of engineering teaching practices and EngE research [8].

In parallel with this ongoing tension, graduate programs offering doctoral degrees in EngE or similar continue to emerge across the U.S. Notably, EngE has grown significantly over the last ten years, with more students pursuing terminal graduate degrees in EngE. As of 2022, 15 programs offered PhDs in EngE or similar disciplines [9]. As more students graduate with terminal degrees in EngE, there is an increasing demand for relevant academic job opportunities. While EngE as a field continues to prioritize both research and teaching, less is known about what skills EngE graduate programs prioritize to prepare students for their futures and how this preparation compares to the expectations of the academic job market.

In this study, we computed sentence embeddings of doctoral program outcomes (POs) and job posting qualifications to evaluate similarity between them. Some prior work uses word embeddings in EngE applications [10], [11]. Some scholars have also used sentence embeddings in various EngE applications, such as to train course syllabi and instructional material [12] and cluster and evaluate student responses to improve open-ended assessment [13]. Scholars have also used sentence embeddings to evaluate the qualifications in job postings [14].

Through our study, we contribute to this growing body of work by integrating qualitative coding techniques with sentence embeddings and cosine similarity to evaluate similarity between two different textual data sources related to EngE doctoral programs and the academic job market. As EngE graduate students committed to the field who are interested in seeking academic jobs after graduation, we selected the graduate EngE space as a test application for an AI technique. We partnered with an industry machine learning engineer who provided AI expertise.

Purpose

This study will demonstrate the utility of integrating qualitative coding, sentence embeddings, and cosine similarity to illuminate similarities and differences between EngE degree-granting programs in terms of their alignment with the EngE academic job market.

Our study will address the following research questions:

1. What are current EngE PhD graduates prepared to do?
2. What academic job opportunities are available in the field of EngE?
3. How do the program outcomes (POs) and the required qualifications of academic job opportunities compare?

Methods

To address our research questions, we undertook an exploratory qualitative study. We employed traditional qualitative data analysis to answer the first two research questions and natural language processing (NLP)-assisted qualitative data analysis to answer the third research question.

Our study uses publicly available data with two primary data sets: program information and job postings. We determined programs and job postings by starting with information posted on a wiki titled The Engineering Education List [15], henceforth referred to as the EngE wiki.

Program Information

First, we identified programs of inquiry. We selected programs that are active, included in the EngE Departments and Programs (Graduate) section of the EngE wiki, based in the United States (U.S.), and offer a doctoral degree in EngE or a closely related discipline (e.g., Engineering and Science Education) as April of 2024. We excluded programs offering only STEM education degrees. Our inclusion and exclusion criteria produced a list of 13 programs across the U.S. We then excluded programs without POs on public-facing documentation. This additional criterion led us to a final list of 12 programs across 12 institutions. We identify these programs in Appendix I. Our preliminary data for each program includes its name, degree name, enrollment size, and POs. We present the geographical distribution of selected doctoral programs in Appendix II and the POs and their categories in Appendix III.

Job Postings

We also downloaded job postings from the EngE wiki on April 8th, 2024, at 4:00 pm. The job posting board on the EngE wiki is updated regularly and provides access to historical job postings for jobs that are no longer available. We looked at all job postings on the page, which included job postings between January 2023 and April 2024. Within each of these posts, we noted the institution, department, location by zip code, and position. We also found the required and desired qualifications for each job using links provided by the EngE wiki. We excluded jobs for which we could not find the original post or the required and desired job qualifications. Using this process, our final job data set includes 95 job postings.

We analyzed both the POs and the job postings. The first and second authors independently qualitatively coded each PO using a list of emergent codes [16]. We conducted a second round of coding to consolidate our original codes and categorize all POs using the codes *career, DEI, discrepancy, engineering expertise, engineering education issues, professional development, research, teaching,* and *other*.

The first and second author also qualitatively coded each job posting using a list of emergent codes to categorize the position title, which were *open rank, assistant professor, associate professor, post doc, director/assistant director, unranked teaching faculty, admin,* and *other*. This process helped us answer RQ1 and RQ2 and conceptualize the findings from RQ3.

Assessing the Alignment of Program Outcomes and Job Responsibilities

To address RQ3, the third author conducted NLP-assisted qualitative data analysis. He computed sentence embeddings of each program's outcomes and the qualifications of each job posting. Sentence embedding models take in a sentence or paragraph as input and generate a single embedding as output [3]. In contrast to simpler word embedding models that map words to numerical values, sentence embedding models capture the contextual meaning of a sentence or paragraph. Cosine similarity measures the similarity between two vectors by taking the cosine of the angle between them. Advantages of using cosine similarity to evaluate embeddings include scale-invariance, interpretability (bounded output between -1 and 1) and applicability to high-dimensional spaces. Natural language processing tasks commonly use cosine similarity to evaluate how similar documents are to one another.

We used the all-MiniLM-L6-v2 sentence embedding model in our analysis. This model was trained on English text from a variety of Internet datasets, including Reddit, Stack Exchange, and Yahoo Answers. It outputs high-quality embeddings for a variety of tasks quickly. We considered other English sentence embedding models like all-MiniLM-L12-v2 and all-mpnet-base-v2 but found that all-MiniLM-L6-v2 offered the best performance for its size, runtime, and computational requirements [17]. To perform our analysis, we embedded POs by creating one sentence embedding per program. We embedded the required and desired qualifications from each job posting by creating one sentence embedding per job posting. Then, we used cosine similarity to quantify the alignment between programs' outcomes and job qualifications. We focused our evaluation on cosine similarity scores above 0.5, since making conclusions about lower cosine similarities can be difficult due to noise in the input and limitations of embedding representations [18].

To ensure quality of our AI methods, we verified the cosine similarity scores using human-in-the-loop or qualitative evaluation [19]. For example, two programs (University of Colorado Boulder and Mississippi State University) in our dataset had nearly identical POs (see Appendix III), so we verified that the cosine similarity between these two programs was close to 1 (i.e., 0.95). First, we computed sentence embeddings of each program's outcomes. Then, we computed cosine similarity between those; we found that the cosine similarity between UC Boulder and Mississippi State POs was 0.95. Next, we checked each program's similarity scores with the job postings. We found that both programs had very close similarity scores to each job posting, with some small differences due to different verbiage in the POs. Overall, these verbiage differences amounted to cosine similarity variation between 0.05 and 0.1, which did not have significant impact on our conclusions about strong versus weak alignment or the utility of this approach.

We used Python, an open-source programming language, to generate maps of our data. Specifically, we used the Folium Python package to create a map locating our selected programs [20]. To generate a heatmap of job posting locations by county, we used the Plotly Python library [21]. Our dataset included the zip code of each institution corresponding to each job posting. We used the zip2fips GitHub repository to translate zip codes to FIPS codes. We plotted these zip codes on the county heatmap [22].

We present a summary of our data analysis process, which integrated qualitative coding, sentence embeddings, and cosine similarity in Figure 1.

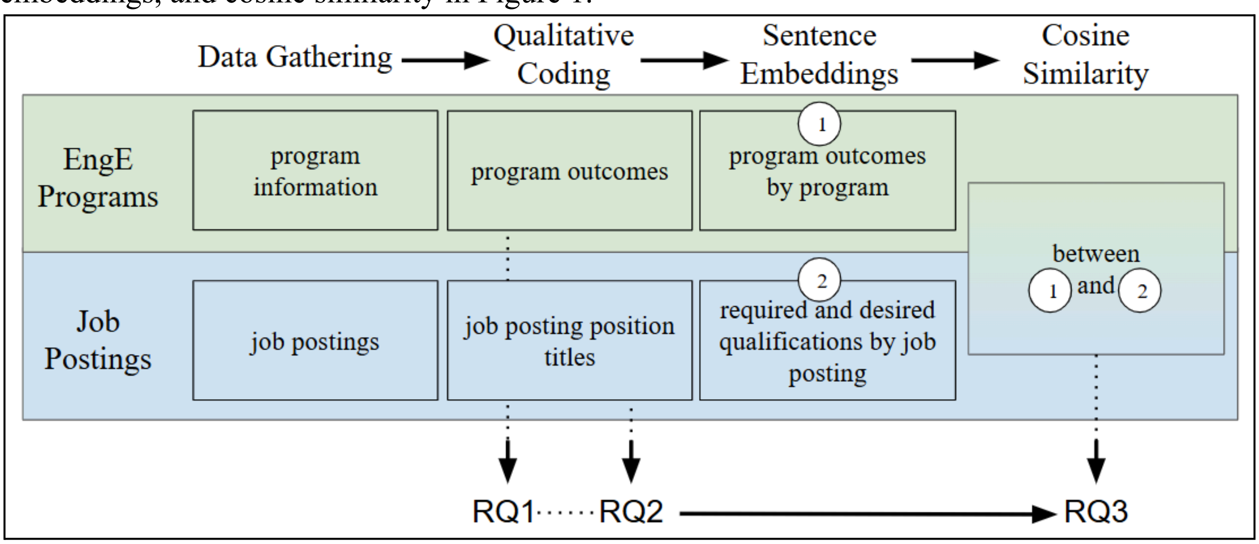

Figure 1: Summary of data analysis process used in study

Positionality

Our research team is composed of two doctoral candidates in EngE and a senior machine learning engineer (MLE). Both doctoral candidates are interested in EngE research and academic positions after graduation. Inspired by reading *The Professor Is In* [23] and completing a graduate course in education assessment, they conducted this research to develop more insight into the role EngE doctoral programs play in preparing students for the academic job market. The senior MLE has no prior experience working in an EngE context but has extensive experience working with embeddings and qualitative textual data.

Limitations

Our study has several limitations related to evaluating programs based on POs, evaluating the job market based on job postings, and using embeddings.

First, we used POs to represent the preparation offered by a graduate program. While POs are useful indicators of graduate program priorities, they are not entirely representative of how graduate programs train and prepare graduate students because doctoral progress is individualized and often based on advisor, department climate, and research group climate [24], [31]. Two students from the same program can experience significant differences in teaching and research experience and students may seek out individual experiences outside of their program to help them prepare for the academic job market. Therefore, our findings about program alignment with job postings are constrained by the fact that POs offer only a partial story about EngE doctoral programs. However, POs are still valuable. POs should drive outcome-driven program assessment, which involves evaluating and aligning coursework, milestones, and assistantships [25].

The job postings we used also present limitations. We used one source for job postings, which compiles academic job opportunities, so we did not capture job titles, position title, and qualifications in other sectors that doctoral students pursue. Within the job postings, we used the required and desired qualifications, which do not necessarily capture the entirety of the position. Additionally, we collected data in April 2024, which means that some job postings from the fall of 2023 were removed. Therefore, our data for job postings did not include some postings typical of an academic recruitment cycle. Furthermore, our data reflects the job market in early 2024 and should not be generalized to the academic job market in any given year.

Finally, there are limitations to our study based on our use of an embedding approach. While our study proves the utility of embeddings to determine high similarity between qualitative data sources, it is not a useful approach to unpack low similarity between qualitative data sources because similarity scores below 0.5 are too noisy to interpret. For our study, approximately one-third of the job posting similarity scores were below 0.5. This leaves some data uninterpreted in our study.

Our study is limited by our chosen scope of POs, one job post forum, and an embeddings approach. Despite these limitations, our study demonstrates that it is possible to integrate qualitative coding, sentence embeddings, and cosine similarity to evaluate qualitative data and that this approach can be useful for other contexts.

Findings

In this section, we present our findings, which are that: 1) EngE doctoral POs are overwhelmingly research and teaching-focused; 2) academic job postings are largely for doctoral entry-level opportunities; and 3) alignment between POs and job posting qualifications vary significantly by program. Our work demonstrates the utility of integrating qualitative coding, sentence embeddings, and cosine similarity for determining alignment between qualitative data sources.

Program outcomes are overwhelmingly research and teaching focused

Through our process of developing and implementing qualitative codes, we found that research and teaching were the most frequent categories of POs. We present the categories, their definition, and count across POs in Table 1.

Table 1: Program outcome categories, definitions, and count across programs

Category	Definition	Count
career	Preparation for and attainment of job/career	4
DEI	Understanding of diversity, equity, inclusion, justice, and belonging	4
discrepancy	Researchers did not agree on a category	6
engineering expertise	Development of disciplinary engineering knowledge and expertise	3
engineering education issues	Development of knowledge related to contemporary issues in EngE	4
professional development	Contributing to service, EngE community development, mentoring, collaborating/working on a team	6
research	Conducting theory, practice, critiquing, writing, presenting	18
teaching	Development of content, assessment, pedagogy, EngE research driven teaching	16
other	Did not fit into an identified category	7

Of the 67 POs, 34 (50%) focused on research or teaching. 21 POs (31%) were in the categories of career, DEI, engineering expertise, engineering education issues, and professional development.

The remaining 13 POs (19%) were not neatly categorized, as we disagreed on the category (6), or the POs did not fit into an identified category and we labeled them as *other* (7). Discrepancy captured two distinct cases. In the first case, one researcher assigned a specific category to the PO and the other researcher labeled it as *other* (4). In the second case, one researcher assigned *DEI*, and the other researcher assigned another category (2), indicating that the PO focused on both DEI and something else. For the POs categorized as *other*, we agreed that these POs did not fit into any other category (7). See Appendix III for the final categorization of each PO.

Notably, PO categories did not evenly distribute across programs. Figure 2 presents the PO categories by program.

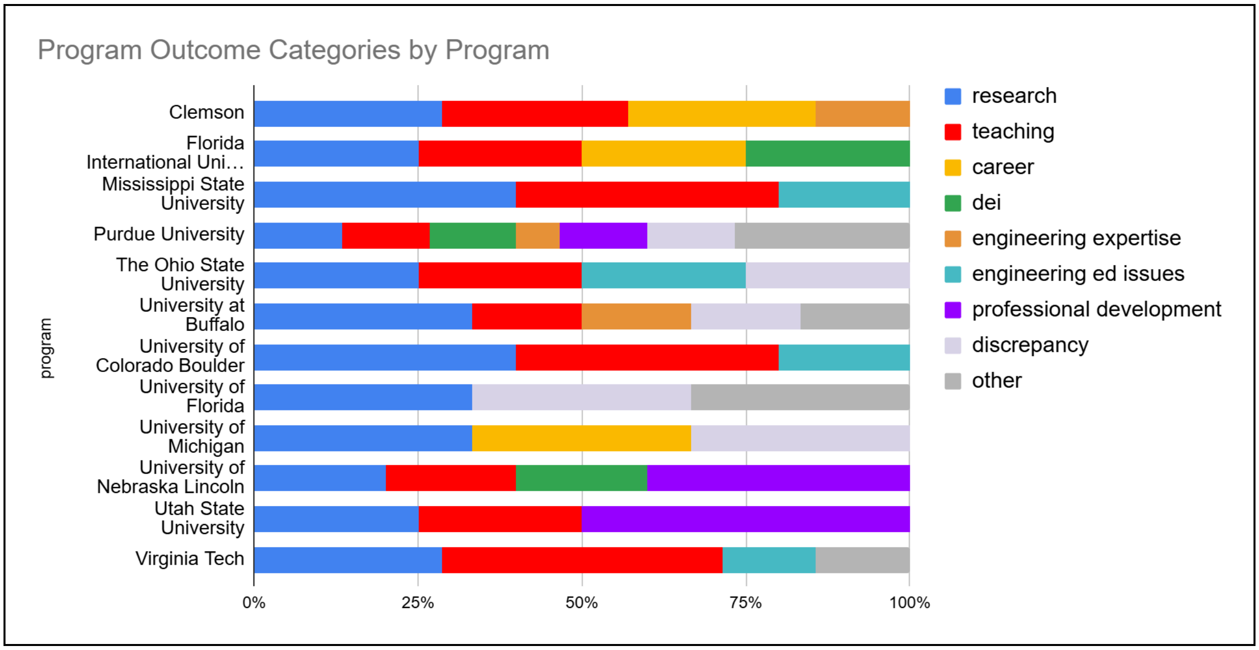

Figure 2: Program Outcome Categories by Program

All programs had at least one research-related PO; however, not all programs had a teaching-focused PO. Ten of the twelve of the EngE doctoral programs had POs focused on research and teaching. Most programs (83%) had outcomes in four or fewer categories.

Academic job postings are largely for doctoral entry-level opportunities

We also uncovered that approximately 70% of the academic job opportunities advertised to EngE graduates are entry-level positions that a recent Ph.D. graduate could successfully achieve, such as postdoc, assistant professor, and teaching faculty positions. In Figure 3, we present the frequency of job postings by job title.

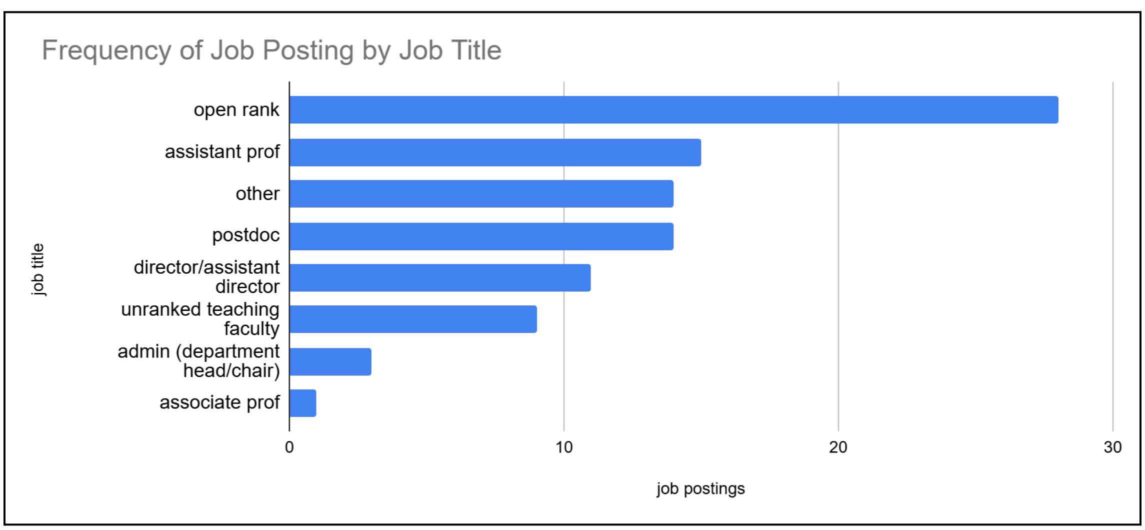

Figure 3: Frequency of Job Postings by Category

Of the 95 job postings, we found that open rank job postings were the most common (29%), followed by assistant professor (16%), other (15%), and postdoc positions (15%).

We also visualized the geographic distribution of job postings by institution, displayed in Figure 4.

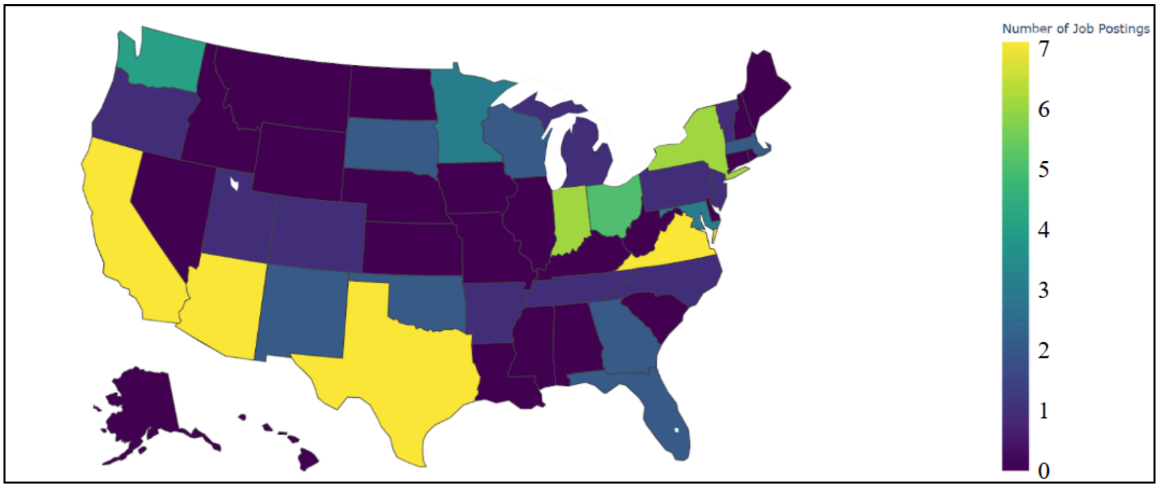

Figure 4: Map of Job Postings

States that offered the most academic jobs for EngE doctoral recipients in 2022 included California, Arizona, Texas, and Virginia.

Alignment between program outcomes and job posting qualifications vary significantly by program

The embedding similarity technique identified cases of strong and weak alignment between programs' outcomes and job posting qualifications. We ranked all programs by highest to lowest similarity scores. We defined the *highest similarity score program* as the program with the highest similarity score between its POs and a given job posting. Based on the ranking generated by the sentence embeddings, we found that certain programs had stronger alignment with recent academic job opportunities, with cosine similarity scores often above 0.70 across many job postings.

We organized our results where each row of our spreadsheet represented a different job posting; the first column that followed the job posting had the program with the highest similarity score for that posting. Each subsequent column was in descending order of similarity score for that specific job posting. We tallied up the programs in the number one spot for each job posting (highest similarity score program) and we display these results in Figure 5 below, color coded by job title.

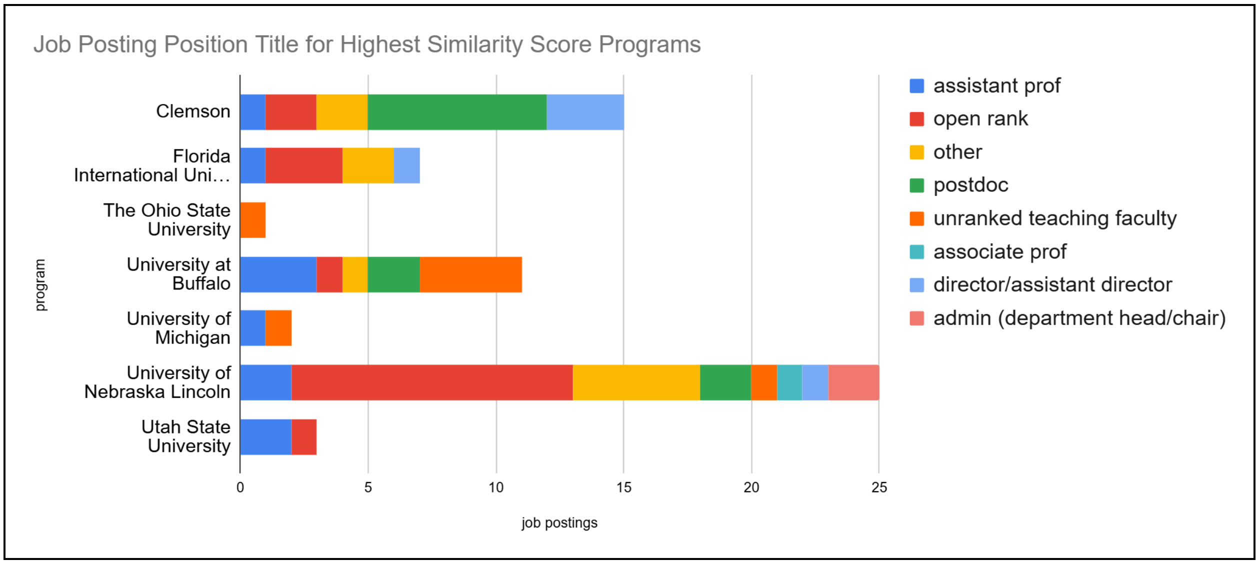

Figure 5: Job Posting Position Title for Highest Similarity Score Programs

Our analysis found that University of Nebraska Lincoln was not only the highest similarity score program the greatest number of times (25), but their POs also aligned with all position titles we identified (8). On the flipside, five programs never had the highest similarity score for a job posting.

For each program, we also identified the number of job postings for which the program's outcomes had a cosine similarity of 0.5 or above. This information is in Appendix IV. Every program had some alignment (cosine similarity ≥ 0.5) with at least 7 job postings. Eleven of the twelve programs had some alignment with at least 22 job postings (33%). It is also notable that a higher number of POs and PO categories did not necessarily correspond to a higher number of aligned job postings.

Discussion and Implications

We used qualitative coding, sentence embeddings, and cosine similarity to establish that EngE doctoral POs are predominantly research and teaching focused, academic job postings are teeming with doctoral entry-level positions, and PO and job posting alignment varies significantly by program. Using embeddings, we evaluated similarity between POs and job postings and further broke down the data by PO categories and job posting position titles.

Our findings suggest that EngE programs, chairs, or department heads can leverage AI-driven techniques to evaluate and refine their current POs against the demands of the current academic job market. Given the wide variation in alignment between POs and job postings, programs should consider regularly reviewing and updating their outcomes to better prepare their graduates for the skills expected for doctoral entry-level positions. Our findings complement existing research documenting that for early-career EngE researcher job postings exist for a variety of roles at various institutional types [26], emphasizing the need for EngE programs to equip graduates with a broad range of skills to prepare them for the job market.

We demonstrated that embeddings and cosine similarity are valuable techniques to augment qualitative data analysis. These methods are valuable in aggregate, rather than looking at individual similarity scores and comparing them. For example, if program 1's outcomes have a similarity score of 0.95 with job posting 1, and program 2's outcomes have a similarity score of 0.93 with job posting 1, we cannot necessarily conclude that university 1 is more aligned with job posting 1 because of noise in the data and limitations of cosine similarity [16]. However, aggregate measures, such as looking at the number of job postings for which the program's outcomes had a cosine similarity of 0.5 or above, allow us to examine which universities' POs had the best alignment generally. Why did we report in Figure 6 the programs that had the *best* alignment with at least one job posting (highest similarity score programs)? This graph represents an aggregate pattern that the University of Nebraska Lincoln had the highest alignment of all programs we examined across *many* job postings. This type of analysis provides an example of how to interpret embeddings and cosine similarity in an aggregate way. Therefore, it is crucial to note that researchers need to do some kind of aggregation on similarity data, and/or have human-in-the-loop evaluation to make conclusions about the data, rather than solely relying on raw scores and rankings of scores.

Our findings suggest that the embedding similarity technique is appropriate and feasible to use in EngE research. Integrating this technique into our traditional qualitative process used in EngE research to analyze a large qualitative data set has made the process significantly more efficient and manageable [10], [27], [28]. Researchers can apply this process to other large-scale qualitative analyses of program documents, course descriptions, structured reflections, or other structured text-based datasets, where identifying broad patterns is the primary goal. We recognize that this type of analysis is better suited for decontextualized data rather than for highly contextualized data, such as interview or focus group transcripts. Highly contextualized data requires deep interpretation, reflexivity, and an understanding of nuances that AI analysis techniques cannot replicate. Thus, AI may reinforce existing biases [29].

In our work, we identified cases of strong and weak alignment between POs and job postings using the embedding similarity technique. In doing so, we demonstrate the potential utility of the embedding similarity method for other applications in EngE research, such as evaluating alignment between course learning outcomes and ABET criteria. Embeddings are becoming more popular in EngE. In a recent study, researchers explored the potential uses of embeddings in EngE research. Their applications included qualitative analysis, course syllabus evaluation, and cross-disciplinary research [30]. Applications like these, as well as comparing course learning outcomes to ABET criteria, focus on identifying patterns, relationships, and alignment on text-based datasets to gain insight that may inform important aspects of EngE, such as curriculum design and accreditation processes, showing its value in EngE research.

Conclusion

In this study we integrated qualitative coding, sentence embeddings, and cosine similarity to evaluate EngE doctoral granting POs and the academic job market. Our study shows promising uses of AI in EngE research, but researchers should involve themselves in the process to ensure that AI results make sense and are meaningful.

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Appendix I

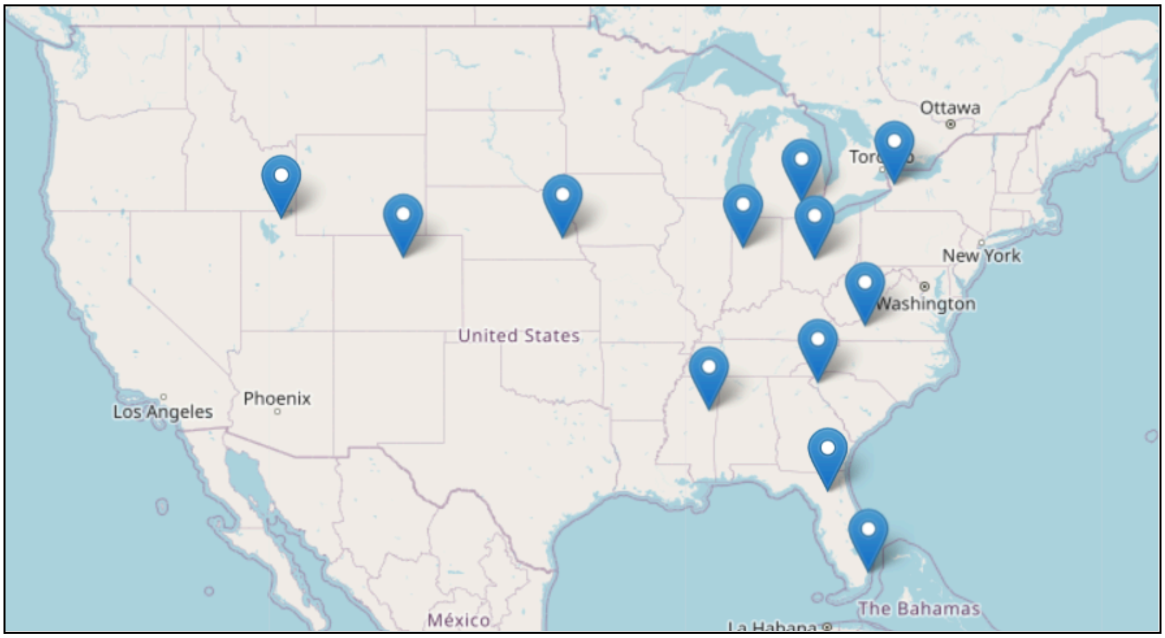
INSTITUTION, TERMINAL DEGREE OFFERED, AND ENROLLMENT

Institution	Zip Code	Degree	2024 PhD Enrollment Size
Clemson	29631	Ph.D. Engineering and Science Education	25
Florida International University	33199	Ph.D. Engineering and Computing Education	19
Mississippi State University	39762	Ph.D. Engineering Education	unknown
Purdue University	47907	Ph.D. Engineering Education	75
The Ohio State University	43210	Ph.D. Engineering Education	24
University at Buffalo	14068	Ph.D. Engineering Education	unknown
University of Colorado Boulder	80309	Ph.D. Engineering Education	unknown
University of Florida	32611	Ph.D. Engineering Education	11
University of Michigan	48109	Ph.D. Engineering Education Research	13
University of Nebraska Lincoln	68588	Ph.D. Engineering Education Research	11
Utah State University	84322	Ph.D. Engineering Education	23
Virginia Tech	24061	Ph.D. Engineering Education	54

Sources: institution webpages

Appendix II

LOCATIONS OF SELECTED ENGINEERING EDUCATION DOCTORAL PROGRAMS IN THE UNITED STATES



Appendix III

PROGRAMS, PROGRAM OUTCOMES, PROGRAM OUTCOME CATEGORIES

Program	Program Outcomes	Categories
Clemson	1. prepare students for academic careers in stem education, science education policy in higher education or informal education institutions, and a range of other careers that 2. graduates from this program will be prepared to become faculty in traditional stem departments, as well as stem education departments. 3. students who enroll in this program will be expected to be (or become) content experts in a stem discipline with at least a master's degree or equivalent in their content area of expertise, either previously completed or earned en route to the PhD. 4. require a deep disciplinary knowledge 5. as well as conduct research in the burgeoning fields of stem education research. 6. coupled with understanding of the factors that affect student learning, retention, and inclusion in stem. 7. they will be prepared to lead curricular and pedagogical reform at the post-secondary level	1. Career 2. Career 3. Engineering Expertise 4. Research 5. Research 6. Teaching 7. Teaching
Florida International University	1. conduct and direct research in engineering or computing education 2. design and assess inclusive, innovative, and effective educational experiences in engineering, computing, and/or engineering and computing education, 3. address critical issues in equity, diversity, and inclusion within engineering and computing education 4. for a diverse set of professional trajectories both inside and outside the classroom.	1. Research 2. Teaching 3. DEI 4. Career
Mississippi State University	1. conduct and direct research in engineering education 2. develop, review, and critique effective research designs 3. effectively teach engineering subjects 4. design and assess engineering programs 5. address critical issues facing engineering education	1. Research 2. Research 3. Teaching 4. Teaching 5. EngE Issues

Purdue University	1. demonstrate in writing an understanding of jedi concepts, issues, terminology, and theories 2. serve on school, college, or university committees focused on jedi or related initiatives, or actively participate in similarly focused initiatives of local, state, regional, or national organizations 3. identify and counteract jedi-related injustices with appropriate evidence 4. demonstrate engineering skills 5. engage in professional development 6. participate actively in professional community 7. synthesize knowledge 8. create knowledge 9. communicate knowledge 10. apply engineering education principles to the solution of instructional or curricular problems 11. teach engineering 12. think critically and reflectively 13. explain and critique education policy 14. develop and implement strategies for teaching, research, and service that purposefully engage self and others in critical conversations pertaining to jedi that include diverse perspectives 15. demonstrate self-reflection resulting in personal growth to improve understanding of self and others	1. DEI 2. DEI 3. DEI 4. Engineering Expertise 5. Professional Development 6. Professional Development 7. Research 8. Research 9. Research 10. Teaching 11. Teaching 12. Other 13. Other 14. Other 15. Other
The Ohio State University	1. identify, discuss, and address critical issues facing engineering education in alignment with stakeholder needs. 2. design, conduct, and critique research in engineering education 3. create, teach, and assess courses and curricula 4. identify, demonstrate, and value appropriate personal and professional skills, mindsets, and traits	1. Engineering Expertise 2. Research 3. Teaching 4. Other
University at Buffalo	1. explain the foundations and describe the history of engineering educational practices. 2. cite and describe research and theory that establish best practices in engineering education.	1. Other 2. Research 3. Teaching

	3. identify and implement best practices for instruction and assessment in the classroom in the context of typical types of engineering courses. 4. read, design and conduct research leading to deeper understanding and innovative utilization of existing knowledge and creation of new knowledge in the field of engineering education. 5. describe and assess critical issues of accessibility, inclusion and diversity in engineering education from the perspectives of student learning and persistence and the overall engineering education enterprise. 6. describe and explain graduate-level topics in an engineering content area	4. Research 5. DEI 6. Engineering Expertise
University of Colorado Boulder	1. conduct and direct research in engineering education. 2. develop, review and critique research designs that study engineering education. 3. learn to effectively teach engineering subjects. 4. design and assess engineering courses. 5. address critical issues facing engineering education	1. Research 2. Research 3. Teaching 4. Teaching 5. EngE Issues
University of Florida	1. proof of one accepted, first-author, peer-reviewed journal article and one conference proceedings paper, approved by the students' supervisory committee chair. 2. one semester of a research to practice experience 3. creation of a reflective engineering education portfolio, which highlights concrete evidence of development of knowledge and skills in the program outcomes throughout a student's graduate work. the portfolio should be discussed with the students' supervisory committee.	1. Research 2. Teaching 3. Other
University of Michigan	1. publish in top tier engineering education and education journals 2. compete for federal grants and contracts 3. enter into multiple career paths.	1. Research 2. Research 3. Career
University of Nebraska Lincoln	1. employ rigorous research skills to critique and make significant contributions to engineering education theory, practice, and policy within an engineering discipline 2. design, implement, and assess research-based pedagogies, curricula, and assessment strategies within and across engineering disciplines and other stem disciplines. 3. lead, communicate, enact the creative spirit, and work in diverse teams to change	1. Research 2. Teaching 3. Professional Development 4. Professional

	education within and across engineering disciplines and other stem disciplines. 4. be an active member in the vibrant local, national, and international community of engineering education researchers with a rich history 5. promote diversity, equity, and inclusion (DEI) in engineering and embed considerations and practices for DEI in all aspects of one's work	Development 5. DEI
Utah State University	1. mentor undergraduate students in developing foundational skills in engineering fundamentals, engineering design, analytical problem solving, computational tools, teamwork, and communication. 2. prepare graduate students to implement evidence-based instructional approaches in student-centered engineering learning environments. 3. lead engineering education research through innovation, creativity, and collaboration. 4. be recognized as a leader through significant contributions of service to the profession of engineering education.	1. Professional Development 2. Teaching 3. Research 4. Professional Development
Virginia Tech	1. identify significant challenges facing engineering education 2. design, conduct, and critique engineering education research 3. understand relationships between sociocultural influences and engineering education & practice 4. translate education research to practice 5. communicate the implications of engineering education research to various stakeholders 6. design and critique assessment plans for engineering-related courses and programs 7. apply pedagogical practices to engineering-related content	1. EngE Issues 2. Research 3. Other 4. Teaching 5. Research 6. Teaching 7. Teaching

Sources: institution webpages

Appendix IV

NUMBER OF PROGRAM OUTCOMES, PROGRAM OUTCOME CATEGORIES, AND SIMILARITY SCORES ≥ 0.5

Program	Number of Program Outcomes	Number of Program Outcome Categories	Number of Similarity Scores ≥ 0.5 between Program Outcomes and Job Postings
University of Nebraska Lincoln	5	4	44
University at Buffalo	6	5	40
Clemson	7	4	37
Utah State University	4	3	36
Florida International University	4	4	35
The Ohio State University	4	3	33
University of Colorado Boulder	5	3	30
Virginia Tech	7	4	26
University of Michigan	3	3	24
Mississippi State University	6	3	22
University of Florida	3	3	22
Purdue University	15	7	7