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Research Article

Developing a correlation matrix to map Program Educational Objectives with Mission Statements using SBERT and Augmentation Techniques

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Abstract:

To ensure coherence between departmental goals and particular program objectives, it is crucial for engineering education to align program education objectives (PEOs) with departmental mission statements. This mapping is done manually, which can be insignificant, time consuming and biased. For the institution to meet its objectives and accreditation requirements, these components must be aligned. With the use of advanced Natural Language Processing (NLP) techniques, particularly sentence-based BERT (SBERT), this study suggests an automated way to map PEOs with departmental mission statements. Since the dataset was limited, we enhanced it by applying text augmentation techniques like synonym replacement, random insertion, deletion, and text shuffling. The dataset was obtained from the Department of Civil Engineering at B.S. Abdur Rahman Crescent Institute of Science and Technology. Cosine similarity is used for fine-tuning SBERT model. It determines the semantic similarity score between PEO and departmental missions and classifies them into high, medium, low, or no similarity based on a threshold values set by experts. Levels of similarity and alternative PEO descriptions for each level of similarity are justified using a rubric system which was created to validate the mapping. The findings show that SBERT can provide a transparent and objective framework for curriculum planning and educational assessment by accurately capturing the semantic relationship between PEOs and departmental mission statements.

1. Introduction

In outcomes-based education, the program educational objectives (PEOs) specify the long-term expected attainments for graduates, also establishing the aspirational vision for the academic programs. Additionally, the departmental mission statements describe the larger mission and values of the department showing the commitment to instruction, research and benefit to society. It is important that PEOs align with departmental missions, to ensure program educational objectives will align with the department's wider vision, which will provide a coherent and organized education program and framework. Alignment of mission and objectives is valued by accreditors such as the National Accreditation Board (NBA) as part of ensuring program educational outcomes support valuable learning experiences and align with program goals. The mapping process has traditionally been a manual process that required time, as well as bias and inconsistency, which are becoming more apparent as institutions expand programs and diversify goal setting. Finding solutions to take inefficient processes and families

managing time, effort, accuracy, and objectivity will be critical to finding innovative solutions.
The incorporation of artificial intelligence (AI) and Natural Language Processing (NLP) is a promising answer to this problem. Developments in NLP, and specifically transformer-based models such as Sentence-BERT (SBERT), have enhanced the capacity to identify semantic patterns among text data. SBERT generates high-quality sentence embedding, making it a beneficial option for tasks such as mapping PEO to Mission. This study provides an artificial intelligence framework to automate the mapping process. This approach uses SBERT to generate embeddings that provide nuanced similarity patterns between the PEOs and mission statements. In addition, the use of a rubric system provides validity and justification of similarity assignments, and the use of data augmentation increased the robustness of the dataset. All of these strategies combined offer a systematic and objective method to align the PEOs to departmental mission.

2. Literature Review

Traditional technology mapping, which usually relies on keyword searches, struggles with the huge scale and diversity of available data, often missing emerging technologies. To address these challenges, Nguyen et al. [1], introduced STARS (Semantic Technology and Retrieval System), an innovative framework that uses Large Language Models (LLMs) and Sentence-BERT to identify the relevant technologies within unstructured data, create detailed company profiles, and rank each firm's technologies based on their operational significance. By combining the entity extraction with Chain-of-Thought prompting and applying the semantic ranking, STARS offer an accurate approach for mapping corporate technology groups. Experimental findings indicate that the STARS significantly enhanced the retrieval accuracy, providing a flexible and high-performing solution for technology mapping across various industries.
[2]. advance S3BERT (Semantically Structured SBERT) to improve how sentence similarity can be interpreted by incorporating Abstract Meaning Representation (AMR) graphs. This study proposes decomposing SBERT embeddings into interpretable semantic subspaces and has features to capture semantic roles, negation, and quantification. Additionally, by implementing AMR metrics and consistency goals, S3BERT maintains the efficiency of SBERT while enhancing transparency. Results from experiments show that S3BERT can maintain strong performance while enhancing understanding for sentence similarity.
Different levels of BERT capture various linguistic attributes. This enables the integration of information from multiple layers to improve sentence representations. Wang et al. [3] examined the layer-specific behaviour of word representations in deep contextualized models. They introduced a novel method for sentence embedding by analysing BERT-based word models through a geometric perspective of the space formed by the word representations. This method is referred to as SBERT-WK. No additional training is necessary for SBERT-WK. They assessed SBERT-WK using semantic textual similarity and other supervised downstream tasks. In addition, ten probing tasks at the sentence level were introduced for comprehensive linguistic analysis. The results indicate that SBERT-WK achieves state-of-the-art performance.
Pijeira-Díaz et al. [4], assess a learning analytics framework utilizing Sentence-BERT (SBERT) to automate assessment of students' causal diagrams. The methodology compares a couple of Dutch BERT-based models (i.e. RobBERT and BERTje), which have been used as classifiers with Support Vector Machine (SVM) and Neural Networks (NN) to predict accuracy of a student's response and to predict timing within the causal chain. The results concluded that SBERT with a SVM technique yielded 86% accuracy for assessment and 92% accuracy for position timing, which surpassed traditional assessments. This work will support a real-time formative feedback loop in teaching, supporting assessment while decreasing the teacher's report responsibilities and providing students with a broader conceptual understanding based on their semantic proximity to their response using a learning process informed by SBERT and machine learning.
Systems theory can help to understand the interactions that occur between PEOs, curriculum, instruction, assessment, and the broader socio-political context [5]. Stakeholder theory entails convincing an organization, including education, to incorporate the interests of all stakeholders into their decision-making. Stakeholder theory enables the study to examine how the multi-sectoral perspectives of educators, students, parents, employers and policymakers might impact the formulation and implementation of PEOs. Stakeholder theory recognizes the value of inclusive and participatory approaches in building a fair and comprehensive educational system [6]. Utilizing both systems and stakeholder theories enhances the analysis by recognizing the principles, motivations, and impacts of PEOs from a multi-

sector perspective. These theories provide valuable conceptual frameworks for examining the details of educational institutions and highlight the significance of factors influencing educational experiences and outcomes.

3. Methodology

Data Collection

We obtained a dataset of PEOs and Mission statements from School of Infrastructure - Civil Engineering Department at B.S. Abdur Rahman Crescent Institute of Science & Technology.

Table 1. *Program Educational Objectives (PEOs)*

PROGRAMME EDUCATIONAL OBJECTIVES	
PEO1	Exhibit expertise in Planning, Design, Execution and Maintenance of Civil Engineering works with environmental care.
PEO2	Design and construct Civil Engineering Infrastructure with emphasis on Durability and Sustainability.
PEO3	Develop and execute Civil Engineering projects with social relevance aiming for rural and urban development.
PEO4	Pursue Research in complex Civil Engineering problems involving multidisciplinary aspects and provide sustainable solutions.
PEO5	Exercise leadership with an ethical approach, perform in teamwork with good communication skills, and excel in cost and time management.

Table 2*: Department Mission Statements*

MISSION	
M1	To offer world-class undergraduate, postgraduate, and research programs of industrial and societal relevance in civil engineering.
M2	To nurture ethically strong civil engineers to address global challenges through quality education and application-oriented research.
M3	To educate students on design, construction, maintenance, and advancements in civil engineering for societal betterment.
M4	To prepare competitive and responsible citizens with good communication, leadership, and managerial skills.
M5	To enhance knowledge through collaborations with global institutions, industries, and research organizations.
M6	To provide a healthy ambience for teaching, research, consultancy, and extension activities.

Text Augmentation: Enhancing Dataset Diversity

To address the problem of a small dataset, we applied a few text augmentation techniques to develop a dataset that is diverse and large for training. These text augmentation techniques ensured that the model would generalize well and manage the different sentences used in PEOs-mission statements. Finally, the augmented dataset provided over 1,00,000 unique PEO-mission pairs. The key augmentation strategies included:

1. **Synonym Replacement**:

   Words in a sentence were changed with synonymous words to produce lexical variation while preserving original constraints. For example, the term "expand" in PEO may be changed with "improve" producing variation in the phrase.

2. **Random Insertion**:

   Other words were added to the sentences to create structural variation. These additions repeated real-world variation in sentence structure and illustrated the model's ability to process slight changes in wordings or an addition of descriptive elements.

3. **Random Deletion**:

   Words were removed from sentences on purpose to make sentences easier and brief. This aspect of augmentation captures the model's ability to derive meaning from incomplete or lack of data; it is something we are often faced with in real-world scenarios.

4. **Text Shuffling**:

   Words and phrases were modified in the sentences to make variations in the text. In this way, the data set demonstrated different ways to maintain the main idea. For example, the concept of "Create sustainable urban roads" could have been represented as "Create urban roads."

Model Training and fine-tuning

To map Program Educational Objectives (PEOs) to Mission statements, we used the Sentence-BERT (SBERT) designed for sentence-level embeddings. The augmented PEO-Mission pairs are used as training data. We used a pre-trained model “paraphrase-MiniLM-L6-v2” which generated high-quality sentence embeddings and fine-tuned it based on our parameters, such as batch size, loss function, epochs, and step size. Therefore, the fine-tuning process optimizes the model for the specific task of identifying and aligning the semantic relationship between Program Education Objectives (PEOs) and mission statements. The key steps and parameters involved in the process are as follows:

1. **Batch Size:**

   Batch size refers to the number of examples handled at once in each forward and backward pass. An appropriate, balanced batch size is selected to maximize computation while keeping model convergence consistent. A small batch size leads to random variability from update to update, while a batch size that is too large requires additional memory to train, as well as being slower than desired.

2. **Loss Function:**

   Cosine similarity loss is used as the main loss function. This choice is due to the fact that the task requires measuring the semantic similarity between sentence embeddings. By minimizing the cosine distance between embeddings of semantically aligned pairs (PEO and mission) and maximizing the distance for unaligned pairs, the model is guided to learn meaningful representations.

3. **Epochs:**

   Fine-tuning is performed for a number of epochs, with each epoch representing a complete pass over the training dataset. After multiple trainings, the model can gradually improve its understanding of the relationship between PEOs and Missions.

4. **Warmup Steps:**

   A warm-up step was introduced to stabilize the learning process in the early stages of training. By gradually increasing the learning rate at the beginning, the model avoids sudden updates that could cause instability. This approach also helps the model enter a stable optimization path before transitioning to a standard learning rate schedule.

Threshold Setting

Fifteen experts classified the similarity scores between the original PEO and the missions of the department as high, medium, low, or no similarity. The qualitative ratings were converted into scores from 0 to 1, where 0 indicated no similarity and 1 indicated high similarity. By making this conversion, the stages of the similarity scores can be classified into more recognizable thresholds in a quantifiable way.

Table 3. *Expert labelled data for PEO1-M1 pair*

PEO-Mission Pair	**Expert 1**	**Expert 2**	**Expert 3**	**Expert 4**	**Expert 5**	**Expert 6**	**Expert 7**	**Expert 8**	**Expert 9**	**Expert 10**	**Expert 11**	**Expert 12**	**Expert 13**	**Expert 14**	**Expert 15**
PEO1-M1	High	High	High	High	High	High	High	High	High	Medium	High	High	High	High	Medium

The pair number identifies the specific PEO1-M1 pair being assessed. For each PEO-mission pair, an expert will assign an overall qualitative similarity label, such as "high", "medium", "low", or "none". To calculate the average numeric score of a pair, the numeric assignments associated with each expert label are summed and divided by the total number of experts involved in the assessment. This process allows us to convert qualitative labels to numeric scores with thresholds set for each qualitative category of high, medium, low, and no similarity. After training the model on augmented PEO-mission pairs, we implement testing using the original dataset. The model classifies the PEO-mission pairs into high, medium, low, or no similarity with respect to the predefined threshold and outputs a mapping of the data that is clear and classified in a straightforward manner.

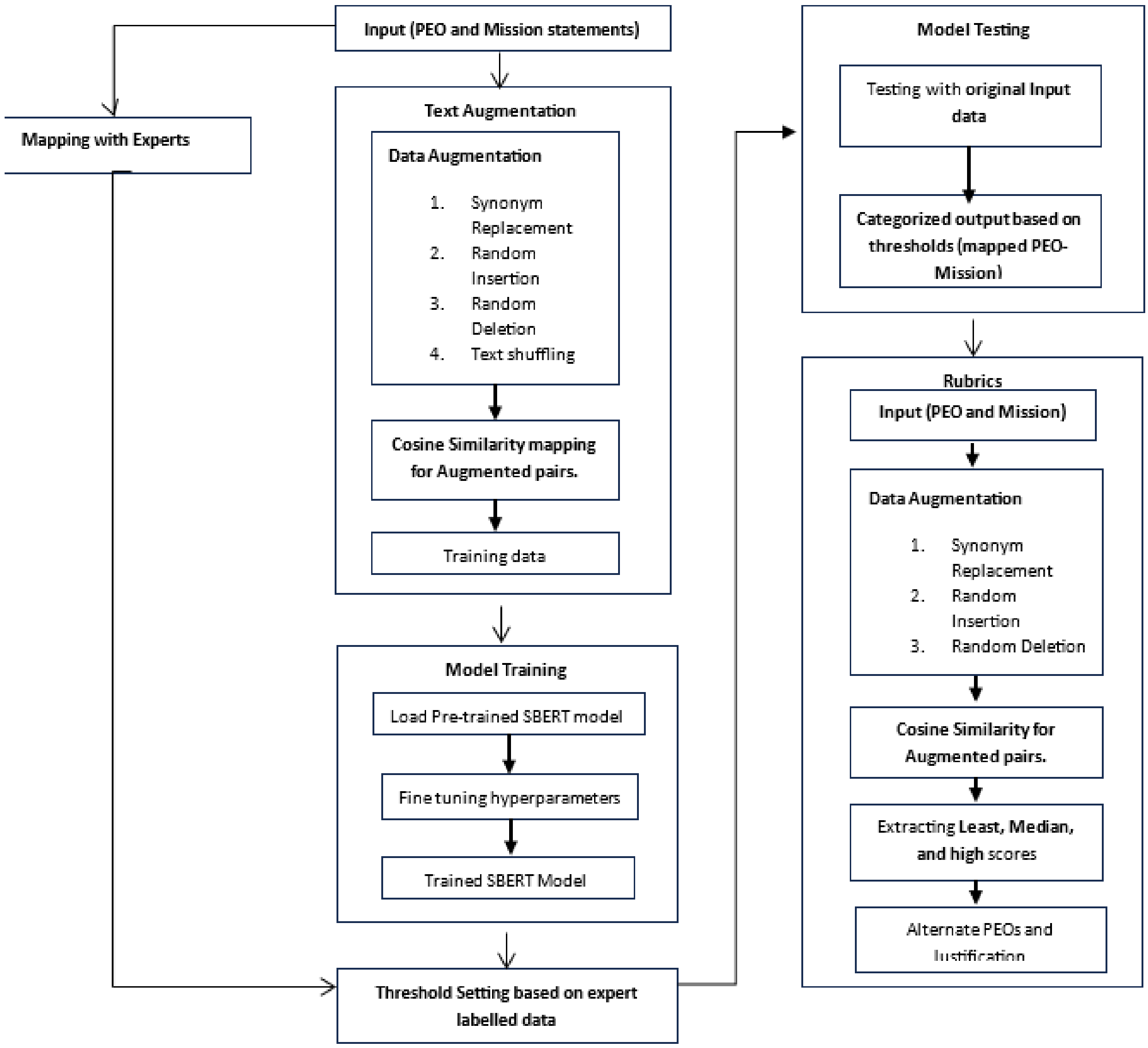
Rubrics

To validate and interpret the model's outputs, rubrics were developed where the model generates alternative PEO statements corresponding to different levels of similarity. Text augmentation techniques, such as random addition, deletion, and synonym replacement, were applied to the original data to create these variations. Each PEO-Mission pair was then analyzed using cosine similarity to identify the pairs with the leaest, median, and highest similarity scores. These identified pairs were used for further justification and to ensure a comprehensive evaluation of the model's performance.

4. Experiments and Results

Data Collection and Augmentation

The data was acquired from the Civil Engineering Department at B.S. Abdur Rahman Crescent Institute of Science & Technology with 5 PEOs and 6 Mission statements, as given in Tables 1 and 2. Since the dataset was minimal and using it to train the model would not be efficient, text augmentation techniques such as Random insertion, Random Deletion, Text Shuffling, and Synonym Replacement were used. The augmented dataset consisted of 250 unique PEOs and 250 unique



Department Missions, resulting in 1,00,000 PEO-Mission pairs for training. The diversity in sentence structure and vocabulary enhanced the model's robustness.

Model Training and fine-tuning

To effectively align Program Educational Objectives (PEOs) with Department Mission, we used the Sentence-BERT (SBERT) model developed for sentence-level embeddings. We chose "paraphrase-MiniLM-L6-v2", a pre-trained SBERT model because of its effectiveness in generating high quality sentence-level embeddings and processing semantic similarity tasks. The model was pre-trained on a large-text corpora and can learn robust language understanding that is required for fine-tuning in particular applications, such as PEO-mission alignment. The pre-training process allowed the model to learn how to interpret different representations of the same educational objectives and outcomes. The fine-tuning of the model was done with a batch size of 16 to optimize for computational ability while enabling the model to learn from examples within every batch. The goal of fine-tuning was to classify PEO - Mission pairs in terms of a high, medium, low, or no level of similarity. We used a cosine similarity loss function to compute the cosine of the angle between the PEO-Mission pair embedding vectors to generate similarity scores between 0 and 1. This function helped the model to assign high similarity scores to closely related pairs and low scores to unrelated pairs. The fine-tuning process covered eight epochs. To ensure training stability, a warmup step was included, during which the learning rate (the step size for updating model parameters) was gradually increased. This warmup phase moderated large, destabilizing parameter updates at the start of training, enabling the model to perform smoothly and achieve optimal performance while minimizing the risk of overshooting.

Table 4. *Fine-tuning*

	Parameters	Values
1	**Batch Size**	16
2	**Loss Function**	Cosine Similarity Loss Function
3	**Training Duration (Epoch)**	8 epochs
4	**Step Size**	10

The training was carried out on Google Colab using an A100 GPU and 16 GB of RAM, which provided the necessary computational resources to fine-tune the SBERT model efficiently. It took about 9 hours to complete.

Converting Qualitative Labels to Quantitative Scores

To implement a more systematic analysis, the qualitative labels provided by the experts on table 3 were converted into numerical values. We assign the following numerical values to each qualitative label:

- **High Similarity** was assigned a score of **1.0.**
- **Medium Similarity** was assigned a score of **0.6.**
- **Low Similarity** was assigned a score of **0.3.**
- **No Similarity** was assigned a score of **0.0.**

This conversion is crucial because it allows us to perform mathematical and statistical analysis on the expert-labelled data. For each PEO-Mission pair, the qualitative labels from all 15 experts were converted to their corresponding quantitative values in Table 3. The average score for each pair was then calculated. This average score represents the consensus among the experts on the similarity between that PEO and Mission.

Table 5. *Quantitative Scores for expert labelled data*

PEO - Mission Pair	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12	Expert 13	Expert 14	Expert 15	Average Score
PEO 1-M1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.6	1.0	1.0	1,0	1.0	0.6	**0.94**

The average similarity score is 0.94, which indicates a high similarity according to our thresholds. This was repeated for all pairs and to set a threshold value for mapping. Calculation for Pair PEO1-M1:

- Expert 1 labelled "High" (1.0), Expert 2 labelled "Medium" (0.6), Expert 3 labelled "High" (1.0), and so on.
- Sum of scores: (1.0 + 0.6 + 1.0 + ... + 1.0) = **14.2**
- Average Score: 13.8 / 15 = **0.94**

This process was repeated for every PEO-Mission pair.

Setting of thresholds

The process of establishing thresholds involved defining cut-off points to categorize similarity scores into High, Medium, Low, and No Similarity levels. This categorization was based on expert evaluations and ensured that the scores accurately reflected the degree of alignment between PEOs and Mission Statements.

High Similarity (0.55 to 1.0):

- **Upper Threshold:** 1.0, representing perfect similarity, indicating highest possible agreement among experts.
- **Lower Threshold:** 0.55, selected as it exceeds the median score and reflects a strong consensus on the close relationship between the PEO and Mission Statements.

Table 6. *Setting of thresholds*

Similarity	Threshold
High	0.55 to 1.0
Medium	0.3 to 0.55
Low	0.1 to 0.3
No Similarity	Less than 0.1

- **Interpretation:** Scores in this range signify that most experts rated the pair as highly similar, ensuring only pairs with strong alignment are labelled as High Similarity.

Medium Similarity (0.3 to 0.55):

- **Upper Threshold:** 0.55, marking the transition from strong to moderate relationships.
- **Lower Threshold:** 0.3, below the median score, reflecting moderate agreement among experts on the relatedness of the PEO and Mission Statements.
- **Interpretation:** Scores in this range indicate a moderate connection, with some consensus among experts, but not enough to classify the pair as strongly aligned.

Low Similarity (0.1 to 0.3):

- **Upper Threshold:** 0.3, distinguishing weak relationships from moderate ones.
- **Lower Threshold:** 0.1, indicating minimal agreement on any relationship.
- **Interpretation:** Scores within this range reflect weak similarity, where only a few experts perceived a connection. These weak links are acknowledged without being mistaken for more meaningful relationships.

No Similarity (0.0 to 0.1):

- **Upper Threshold:** 0.1, representing a lack of meaningful alignment between PEO and Mission Statements.
- **Lower Threshold:** 0.0, indicating an absence of similarity.
- **Interpretation:** Scores in this range reflect general consensus among experts that the PEO and Mission Statements are unrelated, capturing pairs with negligible or no alignment.

Testing the model

The trained SBERT model was evaluated using the original dataset of PEOs and Mission statements from the Civil Engineering Department at B.S. Abdur Rahman Crescent Institute of Science & Technology, as detailed in Table 1. The model-generated similarity scores were classified into High, Medium, Low, and No Similarity categories based on the expert-defined thresholds outlined in Table 6. The resulting mappings produced by the model for these thresholds are presented in Table 7.

Table 7. *Categorized Similarity Scores for PEO-Department Mission Pairs*

PEO-Mission Pair	M1	M2	M3	M4	M5	M6
PEO1	High	High	High	Low	Low	Medium
PEO2	High	High	High	Low	Medium	Medium
PEO3	High	High	Medium	Medium	Medium	Medium
PEO4	High	High	High	Low	Medium	High
PEO5	High	Low	Low	High	Medium	Low

Rubric-Based Evaluation and Justification

To validate and interpret the SBERT model's output, a rubric was developed to provide alternative PEO statements for different similarity levels when mapped with Department Missions. If a PEO-Mission pair was categorized as "High" by the model, the rubric suggests what the PEO statement might look like if it were classified as "Medium," "Low," or "No Similarity." This evaluation framework helps justify the model's decisions and explore the semantic boundaries of its mappings.

To create the rubric, data augmentation techniques such as Random Insertion, Random Deletion, and Synonym Replacement were applied to the original Program Educational Objectives (PEOs) and Department Missions. Each PEO was augmented into 10 unique variations, and the same was done for each Mission. These augmented PEOs were paired with the augmented Missions, and cosine similarity was calculated for each pair. The similarity results were categorized into four levels. The dataset then Extracted Least, Median, and Highest Similarity:

- The **least** similarity pair is the one with the lowest cosine similarity score.
- The **median** similarity pair is the one with the middle cosine similarity score (found by dividing the group into two halves).
- The **highest** similarity pair is the one with the highest cosine similarity score.

This process provided a detailed view of how PEOs align with Missions across various similarity levels, offering insights valuable for program evaluation and curriculum alignment.

For example, in Table 6, the model classified the PEO1-M1 pair as "high" similarity. The rubric provides alternative PEO statements and justifications for why the model did not classify pairs as "medium," "low," or "no similarity." In addition, the rubric also shows how to modify your PEO statements to match these similarity categories. The justification for these alternative mappings is provided to improve the interpretability of model results. An example of the PEO1-M1 mapping is shown in Table 8.

Table 8. *Rubric-Based Evaluation Example for PEO1 and M1*

Similarity Level	PEO Statement	Justification
High	Exhibit expertise in Planning, Design, Execution and Maintenance of Civil Engineering works with	This statement directly aligns with the knowledge and application focus in M1, hence categorized as High.

	environmental care.	
Medium	Exhibit expertise in Planning, Design, and Maintenance of Engineering with environmental care.	This statement is less specific and focuses on proficiency rather than expertise, thus categorized as Medium.
Low	Planning, Design, and Maintenance of Engineering environmental care.	This statement is very general and lacks the depth required for a strong alignment with M1, thus categorized as Low.
No Similarity	-	-

The rubric allowed for the validation of the SBERT model classification for all PEO-mission pairs. We developed alternative PEO statements for each level of similarity and assessed how closely each PEO aligned with the respective missions. When there was no significant agreement, some pairs were classified as "no similarity." Using the rubric approach allowed for clear justification for the model classification. The rubric-based approach provided a clear justification for the model classification and ensured that the mappings were computationally valid and pedagogically sound.

Qualitative Analysis

The similarity scores calculated by the SBERT model were compared with expert-labelled categories, demonstrating strong alignment. A qualitative analysis was carried out to assess the model's ability to capture semantic relationships. The analysis included a manual review of selected PEO-Mission pairs and their respective similarity scores, For instance:

Table 9. *Qualitative Analysis of Selected PEO-Mission Pairs*

PEO	Mission	Calculated Similarity by model	Model calculated Similarity	Expert Similarity
PEO1	M1	0.62	High	High
PEO1	M2	0.57	High	High
PEO1	M3	0.59	High	High
PEO1	M4	0.22	Low	Low
PEO1	M5	0.17	Low	Low
PEO1	M6	0.34	Medium	Medium

5. Discussion

Utilizing an approach based on SBERT presents great promise in streamlining the mapping process between the PEO statements and the department mission statements. When embedding at the text level, this model provides a reproducible and unbiased way to identify semantic similarity. The incorporation of text augmentation strengthens the model's generalization to a different linguistic pattern, resulting in performance invariance across different text structures.

6. Conclusion

This study shows that SBERT can automate PEOs to departmental mission statements, creating a system for efficient and structured training. The rubric-based assessment supports the importance of explicit, descriptive assessment pedagogy but - provides transparency about the decision-making model as well. Evidence provides educators an understanding of how to improve connection of the PEO and mission statement, to ensure program outcomes are meaningful and obtainable in a school development context. Text augmentation techniques improve the model's ability to compare different forms of linguistic structures and improves its overall accuracy; however, other challenges that occur, such as decreased frequency, indicates a need for additional enhancement. Future studies should focus more on advanced NLP models that improve data augmentation techniques, reduce installation errors, and thus improve performance and reliability.

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- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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