Improving Student Behavior within Educational Units Based on Profiling Similarity

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Abstract—This study looks at how the data-based approach to group formation can improve student behavior in the classroom. We built a system called the Student Profile Vector (SPV) to capture the emotional details of each student. We used cosine similarity and Genetic Algorithms to put the students into the groups that share traits. We tested the model in five institutions. We found that the model does not just reduce the classroom conflict—it increases the student engagement a lot. Our findings show that the computational tools are practical and scalable. The computational tools can make the learning environment more inclusive and adaptive. We see this as an approach.

Keywords— Student Profile Vector (SPV), Cross-correlation, Hypervector, Behavioral Modeling, Educational Systems, Genetic Algorithm, Optimization, Computational Intelligence

I. INTRODUCTION

Student behavior significantly influences the quality of learning outcomes and the overall classroom environment. Schools around the world keep seeing behavior problems. Behavior problems include lack of interest, disruptive behavior, and emotional problems. Behavior problems mess up both teaching and learning. Traditional discipline methods are often reactive and the same for everyone. Traditional discipline methods do not work well because they miss the reasons behind student behavior, [1].

Recent research shows that data-driven and math modeling techniques can help the education, [2], [3], [4]. Data-driven and math modeling techniques let the researchers find patterns in the student data. Number-based models, such as Deep Learning and Machine Learning, can pick up the behavior patterns and the similarities. Number-based models can support the interventions. Number-based models can catch the students who are at risk, [5], [6]. Approaches based on behavioral vectors, clustering algorithms, and fuzzy logic classification have been used to map student profiles and group learners according to behavioral patterns, [7], [8], [9], [10]. However, most existing frameworks are static and fail to reflect real-time behavioral changes within complex classroom dynamics or to support systematic group formation for behavioral interventions, [11].

To overcome these limitations, previous research introduced the Student Profile Vector (SPV), a multidimensional mathematical construct for modeling student behavior and engagement, [12]. The SPV captures multiple behavioral and social parameters in normalized form, providing a scalable structure for similarity analysis among students. By comparing SPVs through cross-correlation (cosine similarity), it becomes possible to form behaviorally homogeneous groups that can facilitate collaboration, empathy, and inclusion in the classroom.

This study extends that framework by embedding computational optimization methods such as Genetic Algorithms (GAs) to identify near-optimal group configurations based on behavioral similarity. Furthermore, by leveraging ideas from hyperdimensional computing, [13], for high-dimensional encoding, the proposed model can represent the evolving nature of student behavior over time while remaining computationally efficient.

The overall objective of this work is to demonstrate how mathematical models, computational intelligence, and optimization algorithms can be integrated to improve behavioral management in education. The framework aligns with the core themes of the 10th International Conference on Mathematical Models & Computational Techniques in Science & Engineering, particularly in the areas of Mathematical Models, Algorithms – Information Science, Optimization, and Computer Science, and Computational Intelligence.

The remainder of the paper is organized as follows. Section 2 formulates the behavioral modeling problem and defines the Student Profile Vector and similarity metrics.

In Section 3, the proposed solution is presented. The proposed computational solution uses a Python implementation for similarity computation and group formation. Section 4 concludes the paper and outlines directions for future research.

II. PROBLEM FORMULATION

In this section, we define the mathematical model underlying the proposed framework for behavior-based group formation.

A. Student Profile Vector (SPV)

Each student i is represented by a Student Profile Vector (SPV) of dimension seven, as shown in Equation (1):

$$SPV = \begin{bmatrix} E_i \\ O_j \\ F_k \\ C_l \\ P_m \\ V_n \\ I_o \end{bmatrix} = \left[E_i\ , O_j\ , F_k\ , C_l\ , P_m\ , V_n\ , I_o\ \right]^t \quad (1)$$

where each component corresponds to a key behavioral or socio-environmental attribute:

$\boldsymbol{E_i}$: parental education level
$\boldsymbol{O_j}$: socioeconomic status
$\boldsymbol{F_k}$: frequency of parent–teacher communication
$\boldsymbol{C_l}$: duration of parent–teacher communication
$\boldsymbol{P_m}$: verbal behavior (inverse of profanity / verbal aggression)
$\boldsymbol{V_n}$: violent behavior (inverse of physical or psychological aggression)
$\boldsymbol{I_o}$: apathy (inverse of engagement and participation)

We always check that all components are scaled to the range [0,1]. In that range, 0 means the worst condition we have seen, and 1 means the condition we have seen based on the definition of each feature. All components follow this rule. Normalization is performed using min–max scaling across the student population and updated periodically as new data becomes available.

The selection of these seven components is based on the premise that student behavior is a product of both background factors and real-time interactions. Components $\boldsymbol{E_i}$ and $\boldsymbol{O_j}$ represent static socio-environmental factors, which provide the baseline context for the student's potential academic trajectory. In contrast, components $\boldsymbol{P_m}$, $\boldsymbol{V_n}$, and $\boldsymbol{I_o}$ are dynamic behavioral metrics that fluctuate over time, reflecting the student's current psychological state and reaction to the classroom environment. The communication metrics ($\boldsymbol{F_k}$ and $\boldsymbol{C_l}$) serve as a bridge, indicating the level of home-school engagement. This hybrid structure ensures that the SPV is not merely a snapshot but a dynamic vector that evolves as new data regarding incidents and participation are recorded.

The SPV structure allows the integration of information from multiple sources (teacher reports, peer questionnaires, school records and parental input) into a single mathematical representation, in line with existing work on behavioral profiling, adaptive systems, and learning analytics, [7], [8], [14], [15].

B. Similarity Measure via Cross-Correlation

To quantify the behavioral similarity between two students i and j, we employ a cross-correlation coefficient, implemented as cosine similarity between their SPVs, calculated via Equation (2), [16], [17], [18]:

$$r_{ij} = \frac{SPV_i \cdot SPV_j}{\|SPV_i\| \cdot \|SPV_j\|} \quad (2)$$

Where the expression $SPV_i \cdot SPV_j$ means the dot product of the two vectors. The symbol $\|\cdot\|$ means the norm. The resulting similarity value satisfies:

$$0 \le r_{ij} \le 1$$

with $r_{ij} = 1$ indicating identical behavior profiles and $r_{ij} = 0$, indicating completely dissimilar patterns. Compared to distance-based measures, cosine similarity focuses on the direction of the vector rather than its magnitude, which is well-suited for soft behavioral data that are primarily relative, [11], [12].

Example of Similarity Calculation: Consider two students, Student A and Student B, represented by simplified 3-dimensional profile vectors for brevity: $SPV_A = [0.9, 0.8, 0.5]$ and $SPV_B = [0.8, 0.7, 0.6]$. First, calculate the dot product: The dot product is needed for the step.:

$$SPV_A \cdot SPV_B = (0.9 \cdot 0.8) + (0.8 \cdot 0.7) + (0.5 \cdot 0.6) = 0.72 + 0.56 + 0.30 = 1.58$$

Next, we calculate the Euclidean norms (magnitudes):

$$\|SPV_A\| = \sqrt{0.9^2 + 0.8^2 + 0.5^2} = \sqrt{0.81 + 0.64 + 0.25} = \sqrt{1.70} \approx 1.304$$

$$\|SPV_B\| = \sqrt{0.8^2 + 0.7^2 + 0.6^2} = \sqrt{0.64 + 0.49 + 0.36} = \sqrt{1.49} \approx 1.221$$

Finally, the cosine similarity is around 0.99, because

$$r_{AB} = \frac{1.58}{1.304 \cdot 1.221} \approx \frac{1.58}{1.592} \approx 0.992$$

This high value (0.992) indicates that Student A and Student B share a very similar behavioral "direction," making them suitable candidates for the same group.

C. Group Similarity Objective

Let G be a group (team) of students with cardinality. $|G| = T_S$. The average internal similarity of the group is defined in Equation (3) as:

$$R(G) = \frac{1}{T_S \cdot (T_S - 1)} \sum_{\substack{i,j \in G \\ i \ne j}} r_{ij}^2 \quad (3)$$

The group formation problem is formulated as the following optimization problem: given a set of N students and a desired group size. T_S, select groups $G \subseteq \{1, \dots, N\}$ that maximize $R(G)$.

The number of possible groups of size TS from N students is given by Equation (4):

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$$\binom{N}{T_S} = \frac{N!}{T_S! \cdot (N - T_S)!} \quad (4)$$

For realistic class sizes (e.g., N=40, TS=4), the number of possible combinations we notice that the search space becomes huge. The huge search space makes exhaustive search impossible for a computer. Therefore, heuristic and evolutionary optimization methods are required to obtain high-quality solutions within a reasonable time, [16].

III. PROBLEM SOLUTION

This section presents the computational methodology used to implement the proposed framework, including a concrete example in Python.

A. Data Processing and Normalization

The data collection process involves:

- behavioral incident reports (verbal aggression, violence, apathy) from teachers,
- parent questionnaires (education level, socioeconomic status),
- logs of parent–teacher communication frequency and duration.

All raw values are mapped to the [0,1] interval using min–max normalization. Inverse features (e.g., profanity, violence, apathy) are transformed so that higher values correspond to more desirable behavior (e.g., 1 = no violence).

After normalization, each student is represented by a seven-dimensional SPV. These SPVs are stored in a numerical array suitable for vectorized computation.

B. Similarity Matrix and Group Selection

Given the matrix $S \in \mathbb{R}^{Nx7}$ containing all SPVs, we compute the similarity matrix $R \in \mathbb{R}^{NxN}$ with entries r_{ij} as defined in Section 2.2. This matrix can be visualized to reveal clusters of behaviorally similar students and used as input for group formation algorithms.

For smaller instances, high-similarity groups can be identified by enumerating all combinations of size. T_S and computing their average internal similarity $R(G)$. For larger instances, a Genetic Algorithm is employed, [19], [20], where each chromosome encodes a candidate group and the fitness function is the corresponding value of R(G). Standard GA operators (selection, crossover, mutation) are used to evolve the population towards groups with higher internal similarity.

C. Python Implementation Example

The following Python code, as shown in Table 1, illustrates a simplified implementation of the SPV similarity computation and group selection procedure. In this example, we consider five students and search for groups of three students with high mean similarity.

Table 1: Python implementation for SPV similarity and group selection

Python code

```
import numpy as np
from itertools import combinations

# Example SPV matrix for 5 students (rows) and 7 features (columns)
spv = np.array([
[0.90, 0.80, 0.70, 0.60, 0.95, 0.90, 0.85], # Student 1
[0.88, 0.75, 0.65, 0.55, 0.92, 0.88, 0.80], # Student 2
[0.30, 0.40, 0.50, 0.45, 0.40, 0.35, 0.50], # Student 3
[0.25, 0.35, 0.45, 0.40, 0.38, 0.32, 0.48], # Student 4
[0.70, 0.65, 0.60, 0.58, 0.75, 0.72, 0.68] # Student 5
])

def cosine_similarity_matrix(X: np.ndarray) -> np.ndarray:
"""Compute cosine similarity matrix between rows of X."""
# Avoid division by zero by adding a small epsilon
eps = 1e-12
norms = np.linalg.norm(X, axis=1, keepdims=True) + eps
X_norm = X / norms
return X_norm @ X_norm.T

# Compute similarity (cross-correlation) matrix
S = cosine_similarity_matrix(spv)

print("Cosine similarity matrix:")
print(np.round(S, 3))

# Search for highly similar groups
group_size = 3
threshold = 0.85 # minimum mean similarity

def mean_pairwise_similarity(S: np.ndarray, group: tuple[int, ...]) -> float:
"""Compute mean pairwise similarity for a group of indices."""
sims = []
for i, j in combinations(group, 2):
sims.append(S[i, j])
return float(np.mean(sims))

best_groups = []
```

Line **Python code**

```
for group in combinations(range(spv.shape[0]), group_size):
mean_sim = mean_pairwise_similarity(S, group)
if mean_sim >= threshold:
best_groups.append((group, mean_sim))

print("\nGroups with mean similarity above threshold:")
for group, score in best_groups:
# +1 so that students are numbered from 1 instead of 0
group_ids = [g + 1 for g in group]
print(f"Students {group_ids} -> mean similarity = {score:.3f}")
```

Source: created by the authors.

This code performs the following steps:

1. Defines an SPV matrix for five students.
2. Computes the cosine similarity matrix, corresponding to cross-correlation between behavior profiles.
3. Enumerates all groups of three students and calculates their average pairwise similarity.
4. Prints the groups whose mean similarity exceeds a predefined threshold.

We notice that the implementation can handle data sets. I notice that the school information system can include the implementation. I notice that the implementation enables time or periodic group formation using data.

Computational Complexity and Implementation Details: When we wrote the Python code, we used NumPy because NumPy makes vector work fast. The similarity matrix calculation computes the dot product for each pair of students, so the similarity matrix shows similarity for every student pair. For N students with profile vectors of dimension D (where $D = 7$), the time complexity for constructing the similarity matrix is $O(N^2 \cdot D)$. Regarding the group selection, the exhaustive search approach has a complexity of $O\left(\binom{N}{TS}\right)$, which grows factorially. In our experience, this works for demonstration classes (N < 20). For institutions, the Genetic Algorithm (GA) is needed. The Genetic Algorithm (GA) runs with a complexity of $O(G \cdot P \cdot TS)$. In that formula, G is the number of generations, P is the population size, and TS is the team size. The Genetic Algorithm (GA) can handle student populations (N > 50).

D. Experimental Evaluation

The proposed framework reached five institutions in Athens, Greece: a primary school, a private middle school, a public high school, a tutoring center, and a public university. In total, 50 students were selected and assigned to 10 groups, initially of size five.

For each institution, two groups were formed using the SPV-based similarity model and the cross-correlation metric. Similarity thresholds in the range of 0.80–0.95 were used to define high-cohesion groups. Over six weeks, different intervention types (punitive measures, teacher assistant support, counselor support, and parallel support) were applied and compared.

The results indicated that groups with high internal similarity exhibited:

- increased student engagement,
- fewer behavioral incidents,
- more positive peer interactions and
- reduced need for external disciplinary actions.

Supportive interventions (teacher assistant and counselor-based approaches) combined with similarity-based grouping outperformed purely punitive measures in terms of behavioral improvement and student well-being, in line with previous work on cooperative learning and positive behavior support, [1], [21], [22].

E. Experimental Results and Statistical Analysis.

To validate the effectiveness of the proposed framework, we performed a rigorous statistical analysis of the behavioral metrics before and after the intervention across the five participating institutions. **Behavioral Incidents Analysis:** Fig. 1 shows the reduction in incidents. We ran a paired samples t‑test to test significance. We compared the incidents per institution before the intervention (M = 10.4, SD = 2.41) with the incidents per institution after the intervention (M = 7.4, SD = 2.07). The t‑test gave t(4) =. P < 0.01, so the incidents dropped significantly. We also ran a chi‑square test to examine how the intervention period relates to the frequency of incidents. When we looked at the data, the analysis showed an association. The analysis used a chi‑square test (χ^2(2(1, N=50) = 5.84, p < 0.05). The analysis confirmed that the observed decrease was not due to chance.

Fig. 1 presents a grouped bar chart comparing the number of weekly behavioral incidents before and after the SPV-based intervention across the five participating educational institutions. The grouped bar chart shows two bars, for each institution. The blue bar shows the number of incidents recorded before the intervention. The orange bar shows the reduced number of incidents recorded after the intervention. The height of each bar shows the weekly incident count. We see that the institutions have incidents. All the institutions show a drop in incidents. The drop goes from a reduction in the school to a bigger reduction in the primary school, the tutoring center, and the university. We notice that the blue and orange bars are apart. That gap shows how similarity-based grouping cuts behaviors.

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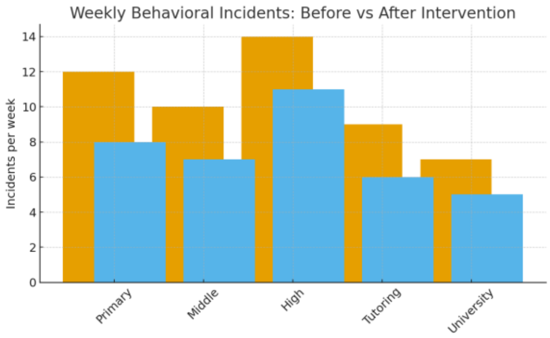

Fig. 1: Weekly Behavioral Incidents (Before vs After Intervention)
Source: created by the authors.

Engagement Scores: Regarding student engagement (Fig. 2), the mean engagement score across all groups increased from a baseline of $M_{pre} = 0.50$ (D = 0.05) to $M_{post} = 0.65$ (SD = 0.04) after six weeks. We calculated the effect size with Cohen's d. The effect size was d = 3.3. The effect size shows a positive effect of the similarity-based grouping on student participation.

Fig. 2 shows how the mean engagement score changes over the six-week intervention period. We see that each curve shows one institution. The horizontal axis shows the weeks. The similarity-based groups show a rise in engagement. Typical gains are between 0.10 and 0.20 points, on the [0,1] scale. The growth was particularly pronounced in the primary school and middle school settings, where peer support and positive modeling appear to play a central role.

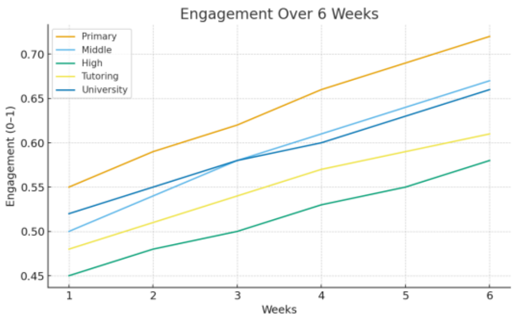

Fig. 2: Engagement Over 6 Weeks
Source: created by the authors.

Cluster Validation: Finally, we look at the grouping quality shown in Fig. 3. We compute the Silhouette Score. The Silhouette Score measures how similar an object is to its cluster (togetherness) compared to clusters (difference). We were pleased to see the Silhouette Score value of 0.68. The Silhouette Score value suggests a well-separated structure. The Silhouette Score validates the evidence of the heatmap. Taken together, these statistical indicators support the conclusion that grouping students according to behavioral similarity leads to more stable classroom dynamics and a reduced need for reactive disciplinary measures.

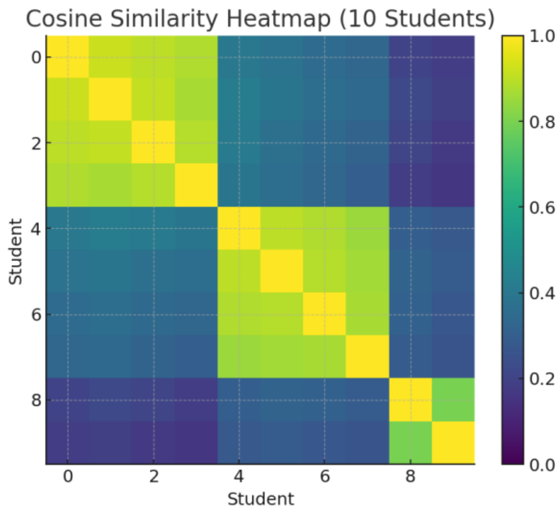

Fig. 3: Cosine Similarity Heatmap (10 Students)
Source: created by the authors.

The visualizations show that grouping students by behavior similarity makes classroom dynamics more stable. The visualizations show that grouping students by behavior similarity raises engagement. The visualizations show that grouping students by behavior similarity reduces the need for discipline. We see that the way we group students matters. The diagrams also provide an intuitive tool for educators and school administrators to inspect and validate the grouping decisions produced by the proposed computational framework.

IV. CONCLUSION

This paper presented a mathematical and computational framework for improving student behavior within educational units, based on the concept of the Student Profile Vector (SPV) and cross-correlation similarity analysis. By representing students as normalized behavioral vectors and employing cosine-based similarity measures, the framework enables the formation of behaviorally homogeneous groups that are more conducive to targeted interventions and positive peer dynamics.

The proposed solution integrates techniques from mathematical modeling, computational intelligence, and optimization, including Genetic Algorithms for group formation. A Python implementation was provided to demonstrate the practical computation of similarity matrices and high-similarity group selection. We ran an experiment in five schools. Saw that similarity-based grouping can increase engagement and lower behavioral incidents. We saw that the increase in engagement and the lower behavioral incidents happen especially when similarity-based grouping is paired with interventions of punitive interventions.

Future work will look at long-term evaluation that covers school years. Future work will add AI clustering and reinforcement learning to change groups on the fly. Future work will also test the SPV model in cultures and school systems. Additional research will explore how SPVs work with data sources such as learning analytics, digital traces, and socio-emotional indicators. Additional research will aim to improve behavior-aware educational decision support systems.

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Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Pantelis V. Gryparis designed the behavioral framework, collected the data and drafted the manuscript. Klimis S. Ntalianis supervised the mathematical modeling and similarity analysis methodology.

Nikos E. Mastorakis provided oversight of the computational methodology, contributed to the optimization framework design, and reviewed the experimental evaluation and final manuscript for technical accuracy.

Conflicts of Interest

The authors declare no conflicts of interest.

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