# Leveraging AI for Effective Teaching: A Machine Learning Approach to Tandem Learning in Mathematics

## Abstract

Educational institutions aim to offer quality education, employing diverse teaching methods like tandem learning. Recognizing the need for personalized approaches, institutions should use data mining techniques to extract insights from educational datasets for optimal predictive model selection for individual students or classrooms. The aim of this study was to evaluate the performance of machine learning (ML) algorithms for predicting student response to tandem learning.

A dataset comprising 89 high school students and 13 predictor variables was utilized. The focus was on a three-state variable that determined whether the student positively responded to the integration of tandem learning into the educational environment. The predictor variables included gender, class, teacher, previous mathematics grade, MBTI variables (extroversion-introversion, sensing-intuition, thinking-feeling, and judging-perceiving), mathematical anxiety, mathematical motivation, qualitative interaction in tandem learning, quantitative interaction in tandem learning, and whether the student outperformed their partner in tandem learning. Nine classification ML algorithms were implemented and the 5 by 2-fold cross-validation with stratified folds was utilized.

Using all predictor variables, Random Forest and K-Nearest Neighbors performed the best, having accuracies of 0.55, and 0.53, and macro F1 scores 0.37, and 0.36 respectively, which is fair considering data balance. Balancing the dataset and using only 2 outcome classes, the performance improved, with the best algorithm being Gradient boosting, performing moderately well (accuracy = 0.59; F1-score = 0.59).

The results imply that machine learning algorithms struggle to accurately predict students' responses to group learning in mathematics using the variables and sample size employed. As a result, they may not be appropriate for aiding teachers in making decisions about selecting teaching methods. Therefore, a simplified approach can yield more effective results, in our case from the transformation of the machine learning classification problem from three states to two.

### Keywords

Assessment, mathematics education, machine learning, tandem learning, teaching methods

### Math subject classification, MSC2020

97D40, 97D60, 62P99

## Introduction

Deep comprehension and knowledge retention are crucial in teaching mathematics (Adler et al., 2014). Recent educational models advocate for indirect learning processes, emphasizing the drawbacks of large classrooms (Mbofana & Banda, 2022; Olasen & Lawal, 2020) and traditional teacher-centered methods (Dervić et al., 2018; Lasry et al., 2014). Small-group learning, including tandem learning where two students collaborate on various activities (Stickler & Emke, 2011; G. Wilson & Blednick, 2011), has been shown to enhance academic achievement (Kalaian & Kasim, 2014), attitudes towards learning (Gaudet et al., 2010), and participation in STEM courses (Wieselmann et al., 2020). It is important to mention that this learning method is not only theoretical and a debate of research since it is used at some level by many teachers (Slavin et al., 2003).

Understanding and effectively mapping students' cognitive and non-cognitive traits, demographic factors, and teacher-related aspects is essential for implementing any teaching method (Gnesdilow et al., 2013; Kurniawati et al., 2023; Li et al., 2021; Puklek, 2001; Van Der Laan Smith & Spindle, 2007; Van Diggele et al., 2020). It is crucial to recognize the appropriate conditions for the application of such learning methods to maximize their positive impact on student outcomes. The recent advancements in artificial intelligence (AI), particularly machine learning (ML) based algorithms, offer unique opportunities for researchers to predict personalized education outcomes through the analysis of heterogeneous data (Sekeroglu et al., 2019; Yağcı, 2022). The success of these models relies on their interpretability, replicability, and generalizability, and there is a growing trend to enhance these aspects (Rastrollo-Guerrero et al., 2020).

While there is an increasing use of ML/AI models to predict overall student success in education (Ho et al., 2021; Ibarra-Vazquez et al., 2023; Luan & Tsai, 2021; Musso et al., 2020; Yağcı, 2022), their applicability in evaluating the effectiveness of specific teaching methods, especially collaborative formats like tandem learning, remains limited. This study bridges that gap by integrating machine learning with tandem learning, motivated by the need to align pedagogical innovation with data-driven personalization. Tandem learning promotes peer collaboration and interpersonal interaction, yet predicting its effectiveness on an individual level is complex. Machine learning offers a promising approach to model this variability, particularly when grounded in constructivist learning theory and personalized learning paradigms, which emphasize learner agency and context-sensitive strategies (Taylor et al., 2024; Villegas-Ch et al., 2024). Therefore, this study aims to address this gap by developing machine-learning models using a Slovene dataset (*N* = 89). These models will predict the personalized success of tandem learning based on various demographic factors, teacher-related factors, as well as cognitive and non-cognitive factors. The aim of the research is, therefore, to shed light on which ML algorithms perform the best and are the most accurate in predicting the effectiveness of tandem learning considering 13 features, including gender, class, teacher, previous mathematics grade, MBTI variables (extroversion-introversion, sensing-intuition, thinking-feeling, and judging-perceiving), mathematical anxiety, mathematical motivation, qualitative interaction in tandem learning, quantitative interaction in tandem learning, and whether the student outperformed their partner in tandem learning. Having a deeper understanding of which algorithm is the most accurate in predicting the effectiveness of applying the tandem learning format might help educators and researchers to adopt new methods, based on ML, to analyze data and implement tailored learning and teaching methods.

## Theoretical framework

### 2.1 Tandem learning

Recent trends to develop and use alternative, indirect forms of educational processes (Arias & Peralta, 2011; Blažič et al., 2003). This is driven by the belief that such approaches are more effective in fostering improved academic achievement (S. Wang et al., 2023). This is driven by the belief that such approaches are more effective in fostering improved academic achievement (Kalaian & Kasim, 2014), developing more positive attitudes toward learning (Gaudet et al., 2010; Hillyard et al., 2010), and enhancing persistence in STEM courses and programs (Kalaian et al., 2018; Micari et al., 2010; Wieselmann et al., 2020; S. Wilson & Varma-Nelson, 2016).

One notable small-group learning practice among these alternatives is tandem learning. This unique approach involves pairs of students conducting experiments together, formulating reports, solving problems, and so forth (Stickler & Emke, 2011; Tomić, 2002; G. Wilson & Blednick, 2011). Tandem learning stands out for its simplicity from an organizational standpoint, offering increased opportunities for active engagement compared to frontal and group teaching methods. Importantly, it provides a middle ground between the collaborative nature of group learning and the individualized approach of solo learning (Blažič et al., 2003).

The implementation of group learning serves to accomplish five significant objectives, as articulated by Peklaj (2001): (1) facilitating mutual understanding among students, (2) fostering a sense of group identity, (3) promoting peer support, (4) cultivating an appreciation for differences among group members, and (5) instilling characteristics of teamwork. This approach closely aligns with the five fundamental components of cooperative learning as outlined by Johnson et al. (1991), namely (1) positive interdependence, where students rely on each other for success; (2) face-to-face promotive interaction, encouraging constructive communication; (3) individual accountability and personal responsibility, ensuring active participation of each student; (4) regular utilization of interpersonal and small group social skills; and (5) consistent, periodic evaluation of group dynamics and performance. By embracing these principles, educators can better equip their students with the social and interpersonal competencies essential for success in the contemporary world. Slavin et al. (2003) identified four significant theoretical perspectives on the achievement effects of cooperative learning: (1) motivationalist, (2) social cohesion, (3) cognitive-developmental, and (4) cognitive-elaboration. The last two focus on the interaction among groups of students, and all four perspectives can be viewed as complementary.

### 2.2 Machine learning and classification

Data mining is the process of uncovering hidden patterns, relationships, or insights within vast datasets through techniques from statistics and database management (Baradwaj & Pal, 2012). It involves data preprocessing to prepare information for analysis and utilizes methods such as clustering and association rule mining (Singhal & Jena, 2013). In contrast, ML, a subset of AI, focuses on building predictive models by allowing computers to learn from data and make decisions or predictions (Candanedo et al., 2018). The sequences of steps identified in extracting knowledge from data are shown in Figure 1 below.

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Figure : Knowledge discovery process.

ML encompasses various learning paradigms, including the classification process, and finds applications in areas like recommendation systems. Classification, a fundamental task in both data mining and ML, involves categorizing data into predefined classes, such as binary or three-state classification, based on patterns learned from labeled data. This classification process is employed in various domains, such as healthcare and sentiment analysis, which includes educational sciences (Shaik et al., 2023), to make data-driven decisions (Baradwaj & Pal, 2012).

Classification in ML is a pivotal process where the primary goal is to train a model to assign predefined labels or categories to new, unseen instances based on patterns identified during the learning phase (Charbuty & Abdulazeez, 2021). It relies on the extraction of features from the input data, which are then used to make predictions about the class to which a particular instance belongs. This process involves both supervised learning, where the model is trained on labeled data, and unsupervised learning, where the model must identify patterns in unlabeled data (Berry et al., 2020).

Sentiment analysis, as mentioned in the context of educational sciences, is a specific application of classification in natural language processing (Mite-Baidal et al., 2018). This involves determining the sentiment expressed in textual data, such as reviews, social media posts, or survey responses. By classifying sentiments into categories like positive, negative, or neutral, organizations can gain valuable insights into public opinion and tailor their strategies accordingly.

### 2.3 Connecting tandem learning and machine learning

Technologies can be considered in terms of whether they are mainly student teaching (with a primarily instructionist approach), student supporting (primarily constructivist approach), or teacher supporting (which primarily helps teachers do tasks they already do but faster or with less effort) (Holmes et al., 2019).

Beyond its broader applications, ML has been harnessed to precisely forecast student success (Abana, 2019; Kotsiantis et al., 2004; Ofori et al., 2020; Qazdar et al., 2019; Rastrollo-Guerrero et al., 2020; Yakubu & Abubakar, 2022), identify at-risk learners (Adnan et al., 2021; Chui et al., 2020), and tailor educational interventions (Luan & Tsai, 2021; Stimpson & Cummings, 2014; Tsai et al., 2020; Yang, 2021), particularly within mathematics education (Hwang & Tu, 2021). These applications often rely on performance indicators, behavioral data from learning management systems, or psychometric assessments. The concept of “learning analytics” was introduced and demonstrated by other studies (Bhusal, 2021; Cortez & Silva, 2008; Siemens & Gasevic, 2012), before the widespread use of ML, which used weaker statistical methods. Aside from forecasting success, ML can help us identify the most important variables that affect said forecast (Lu et al., 2020; Luan & Tsai, 2021). Multiple studies have delved into the analysis of crucial features in the learning environment (Bregant et al., 2025; Hodges, 2018; Humphrey et al., 2009; Moradi et al., 2018; Scribner & Donaldson, 2001), however only a few have harnessed the power of modern algorithms, such as ML, which hold the potential for significantly enhanced sight. Therefore, it is of paramount importance to explore in great detail the feature selection problem.

## Empirical work

The present research was conducted as the effectiveness of tandem learning in high school mathematics remains unclear due to the complexity of numerous variables influencing its success.

This study aims to leverage three-state classification machine learning algorithms to analyze multifaceted variables to determine the successfulness of a tandem learning environment.

Given the scarcity of comprehensive studies employing ML algorithms to assess teaching method selections, this research acknowledges the potential limitations in drawing definitive conclusions. While aiming to discern patterns of predicting the success of tandem learning environment, this study will consider the need for a cautious interpretation of results. Even in the absence of conclusive findings, insights gathered from the analysis will contribute to the ongoing discourse on the efficacy of tandem learning in mathematics education. Therefore we hypothesize that even when feeding ML models with diverse data sets encompassing student profiles and collaborative dynamics, some algorithms will perform sub par, while others may perform fair.

### 3.1 Methodology

In the present research, the causal non-experimental method of pedagogical research is applied.

### 3.2 Sample

In this retrospective study, we used a dataset gathered at a high school in Slovenia, which is publicly available at (Author, 2023). The sample comprised 89 11th- and 12th-grade students of a Slovenian Gymnasium (i.e., high school); 28 males and 61 females. The topics covered during the tandem learning sessions were vectors for 11th-grade students and conic sections for 12th-grade students. While informative, the relatively small sample size may limit generalizability and affect the performance stability of machine learning models.

Participants in the study engaged in tandem learning for about a week during class time, with no randomization in pairings. The structure involved a mix of regular classroom activities and tandem learning sessions, with students seated in pairs at two-seat desks. The efficacy of tandem learning was measured across various factors, categorized into demographic, psychological, and tandem-learning-related variables (see section 3.5.1).

### 3.3 Data preprocessing and data analysis

The gathered data was analysed using Python programming language, primarily using *pandas* (version 2.1.3) and *scikit-learn* (version 1.3.2) libraries. ML code, as well as variable importance and other data analysis notebooks, are openly accessible at (Author, 2023).

Dataset was already in the form of tidy data (Wickham, 2014). Categorical variables, which were a priori encoded using label encoding were transformed into dummy variables using one-hot as most ML algorithms require numerical input and do not handle well numerical data, that is not continuous (Tan & Pu, 2023; Wu et al., 2020).

We implemented nine ML algorithms, chosen for their effectiveness in classification tasks and their ability to perform three-state classification (see references at each algorithm). These models were selected to explore a range of approaches—including probabilistic, instance-based, linear, and ensemble methods—and to assess their comparative performance i.e. their capability of predict correctly the effectiveness of tandem learning in the context of a relatively small and moderately complex dataset. This variety also allows us to evaluate which types of models may be more robust in low-sample educational settings, acknowledging that the small dataset size likely impacts classification accuracy.

Naive Bayes (NB; Frank et al., 2000): it is a probabilitstic classifier based on Bayes' theorem and it assumes independence among features;

k-Nearest Neighbors (k-NN; Zhang, 2016): it is a non-parametric and instance-based learning algorithm which classifies data points on the majority class of their k-nearest neighbors. It is effective in classification and it is sensitive to the choice of the distance metric;

Decision Tree (Charbuty & Abdulazeez, 2021): it is a hierarchical tree-like structure that represents decisions based on features; it is easily interpretable, however it is prone to overfitting;

Logistic Regression Models with OvA strategy (LR; Sun et al., 2019): It is a binary classification algorithm used to predict the probability of an instance belonging to a particular class. However, when dealing with multi-class classification problems (more than two classes), the one-vs-all (OvA) strategy, also known as one-vs-rest (OvR), is often employed. The OvA strategy involves training three separate binary logistic regression models. Each model is designed to distinguish one class from the combination of the other two;

Linear Discriminant Analysis (LDA; Xanthopoulos et al., 2013): it is a classification algorithm seeking to find linear combinations of features that best separates classes; it is useful in dimensionality reduction and feature extraction, but it assumes normally distributed classes and equal covarances;

AdaBoost (with 1000 estimators; Schapire, 2003): it is an ensemble learning method that combines weak classifiers to create a strong classifier; it gives more weight to misclassified instances which improves the overall performance of the algorithm; it is also effective in boosting the performance of decision trees;

Gradient Boosting (GB with 1000 estimators; Natekin & Knoll, 2013): it is an ensemble technique that builds trees sequentially, with each tree correcting the errors of the previous one; it often emplyes decision trees as weak learners; it is a robust and widely used classification technique;

Support Vector Machine (SVM with RBF kernel; Suthaharan, 2016): it is a powerful algorithm for classification which constructs a hyperplane that maximally separates the classes; it is effective in high-dimensional spaces and can handle non-linear relationships through kernel functions;

Random Forest (RF with 1000 estimators; Rodriguez-Galiano et al., 2015): it is an ensemble learning method that builds multiple decision trees and combines their predictions while reducing overfitting and improving accuracy compared to individual trees; it is widely used in classification tasks.

Said algorithms are capable of performing 3-state classification. Models were evaluated using 5x2 cross-validation (CV) with stratified folds (Cieslak & Chawla, 2008) with the main metric of performance evaluation being macro F1-score through average fold repetition (Chicco & Jurman, 2020). The 5x2-CV is a technique that splits datasets into two subsets (folds), and the model is trained and tested on these subsets. The process is repeated five times, resulting in 10 overall evaluations. The final performance metric is the average of the performance metrics obtained from the ten evaluations. This method helps to reduce the variability that might arise from a single random split and provides more reliable estimates of the model’s performance. This method assesses how well a ML model generalizes unseen data and helps prevent overfitting. It is useful when the dataset is limited (Raschka, 2018). F1-score is a metric commonly used to evaluate the performance of a classification model, specifically when dealing with unbalanced datasets (Chicco & Jurman, 2020). It is the harmonic mean of precision () and recall (), ranging from 0 to 1, with higher values indicating better model performance (L. Wang et al., 2021). In the multi-class case, we must consider all the classes i.e. all the entries of the confusion matrix. To do so, we require a multi-class measure of precision and recall to be inserted into the harmonic mean. Such metrics may have two different specifications, giving rise to two different metrics: Micro F1-Score and Macro F1-Score (Opitz & Burst, 2019). The F1 macro score in a multi-class scenario involves computing Macro-Precision and Macro-Recall by averaging precision for each predicted class and recall for each actual class. In Macro F1-Score, all classes carry equal weight in the calculation, eliminating distinctions between highly and poorly populated classes (Grandini et al., 2020).

Additionally, the t-distributed stochastic neighbor embedding (t-SNE; Van der Maaten & Hinton, 2008) was employed in this research. The t-SNE is an ML algorithm commonly used for dimensionality reduction and visualization of high-dimensional data in a lower-dimensional space. It is particularly effective in revealing the underlying structure and patterns within the data, making it valuable for exploratory data analysis and visualization tasks. t-SNE works by modeling the similarity between data points in the high-dimensional space and the low-dimensional space. The algorithm focuses on preserving the pairwise similarities between data points, emphasizing the preservation of local relationships rather than global ones. t-SNE is a non-linear technique, meaning it can capture complex relationships between data points that linear methods might struggle to represent accurately. The t-SNE technique aims to retain the local structures and similarities between nearby data points in the original high-dimensional space. This is especially useful for visualizing clusters and patterns in the data.

### 3.4 Previous findings on the used dataset

The dataset used in this study comprises 14 variables derived from a total of 56 survey items administered after a one-week implementation of tandem learning. Data were collected through standardized instruments, including the OEJTS for MBTI personality traits, the AMAS for mathematics anxiety, and a shortened version of the ATMI for motivation. Other variables, such as gender, teacher, class, and recent math grades, were recorded from school records. Tandem-specific variables—qualitative and quantitative interaction, and relative performance—were gathered via self-reported Likert-scale items, reflecting students’ perceptions during the tandem learning sessions​. The selection of variables in the ML models was theoretically informed and based on the framework outlined in Author (2024), which emphasizes demographic, psychological, and tandem-specific factors as critical dimensions influencing the effectiveness of tandem learning.

In our research, we utilized a pre-analyzed dataset, as explored by (Author, 2024). The internal consistency of variables, assessed through instruments comprising multiple items, was previously examined with Cronbach alpha being used for variables (1) Anxiety, (2) Motivation, (3) Introversion, (4) Sensing, (5) Feeling, and (6) Judging all of them having fair results.

Moreover, feature importance was performed using Mutual information and recursive feature elimination in regards to logistic regression, highlighting that variables related to tandem learning held the utmost significance, followed by variables in a general context, and lastly, variables associated with students' psychological profiles. Key predictors for student responses were identified, with outperforming partner, class, and qualitative interaction within groups being the most influential, as indicated by mutual information scores. Recursive feature analysis underscored the importance of qualitative interaction, outperforming partner, and gender as primary predictors.

In addition, correlation analysis using Spearman ρ (all variables were analyzed with the Shapiro-Wilk test as normally distributed) unveiled meaningful relationships within the dataset. The three most positively correlated pairs were gender-anxiety, interaction qualitative-interaction quantitative, and grade-motivation, while the most negatively correlated pairs were motivation-anxiety, gender-feeling, and gender-motivation. All correlation coefficients exhibited a moderate strength of association.

### 3.5 Results

#### 3.5.1 Student sample and variables used

The target variable was a three-state measure of successfulness on a 3-levels Likert scale (“successful”, “neutral”, “not successful”), both regarding academic performance as well as general wellbeing during the implementation of tandem learning. The predictors were variables in (1) general sense (gender, class, teacher, previous mathematics grade), (2) psychological sense (MBTI variables: extroversion-introversion, sensing-intuition, thinking-feeling and judging-perceiving, and other variables: mathematical anxiety and motivation), and (3) tandem-learning-related variables (qualitative interaction, quantitative interaction, and whether student outperformed their partner). All variables provided were used for ML purposes. Their descriptive statistics can be found in Table 1, Table 2, and Figure 2.

Table : Dataset description of tandem-learning-related, and general variables used. The categorical variables, initially label encoded, were transformed using one-hot encoding, generating dummy variables, as that is needed for ML algorithms used (see references in section 3.3.). Ordinal variables assessed using Likert scales are also described utilizing measures of central tendency due to their inherent numerical order and range.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Successfulness | Grade | Interaction  quantitative | Interaction  qualitative | Outperforming  partner | Class | Teacher | Gender | |
| *M* | 2.4 | 3.4 | 2.2 | 2.1 | 2.1 | Categorical  (7 options) | Categorical  (4 options) | Categorical  (2 options) |
| *SD* | 0.6 | 1.0 | 0.7 | 0.7 | 0.6 |
| *min* | 1.0 | 2.0 | 1.0 | 1.0 | 1.0 |
| 25% | 2.0 | 3.0 | 2.0 | 2.0 | 2.0 |
| 50% | 2.0 | 3.0 | 2.0 | 2.0 | 2.0 |
| 75% | 3.0 | 4.0 | 3.0 | 3.0 | 2.0 |
| *max* | 3.0 | 5.0 | 3.0 | 3.0 | 3.0 |

Note. M = mean, SD = standard deviation.

Table : Dataset description of psychological variables. All variables belonging to this type were treated as continuous.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Anxiety | Motivation | Introversion | Sensing | Feeling | Judging |
| *M* | 25.8 | 20.4 | 20.6 | 22.7 | 23.3 | 22.8 |
| *SD* | 6.8 | 6.3 | 5.6 | 4.5 | 4.7 | 5.7 |
| *min* | 10.0 | 7.0 | 8.0 | 12.0 | 9.0 | 9.0 |
| 25% | 21.0 | 16.0 | 16.0 | 20.0 | 20.0 | 20.0 |
| 50% | 26.0 | 20.0 | 21.0 | 23.0 | 23.0 | 23.0 |
| 75% | 31.0 | 24.0 | 24.0 | 25.0 | 26.0 | 26.0 |
| *max* | 40.0 | 34.0 | 37.0 | 35.0 | 35.0 | 37.0 |

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Figure 2: Variables used.

For ML purposes that follow it is important to know that the target variable was not balanced with represented classes being 6, 39, and 44, indicating the population distribution across the ordinal classes 0, 1, and 2, respectively, on a Likert scale. Therefore, the usage of the F1-score for the assessment of the model’s performance was deemed suitable (Chicco & Jurman, 2020; Wang et al., 2021). For baseline reference, we consider a simple model that predicts the majority class for all instances, resulting in an accuracy of 44 (representing the largest class) out of 89 (total samples), equivalent to 49%. However, it is crucial to note that the evaluation metric after surpassing this baseline would be the F1-score, providing a more nuanced assessment of the model's performance in handling imbalanced class distributions. Subsequently, we transitioned to a two-state classification by merging classes 0 (“not successful”) and 1 (“neutral”). Finally, we reintroduced the three-state classification, but this time with a reduced set of variables, based on their predicting strength as seen in literature, to enhance the model performance. Notably, throughout this process, we refrained from dropping variables and merging classes simultaneously.

#### 3.5.2 Model performance

According to the F1-metric, the two models with generally better performances in our experiments were RF and k-NN. Their performances are fair, as their accuracy was still better than a number of samples in the majority class (49.4%). Therefore the models outperform the baseline. Other models performed worse, their poor performance indicating they might not be learning the underlying patterns effectively. The classification of individual ML techniques is presented in Table 3.

Table : Classification result.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classifier | Accuracy | Precision\_macro | Recall\_macro | F1\_macro |
| NB | 0.34 | 0.41 | 0.39 | 0.30 |
| k-NN | 0.53 | 0.36 | 0.38 | 0.36 |
| Decision Tree | 0.44 | 0.36 | 0.47 | 0.33 |
| LR | 0.48 | 0.33 | 0.34 | 0.33 |
| LDA | 0.44 | 0.31 | 0.31 | 0.31 |
| AdaBoost | 0.39 | 0.27 | 0.28 | 0.27 |
| GB | 0.46 | 0.32 | 0.33 | 0.32 |
| SVM | 0.45 | 0.16 | 0.30 | 0.21 |
| RF | 0.55 | 0.38 | 0.39 | 0.37 |

In analyzing the model's performance, the plotted confusion matrices, as shown in Figure 3 provide a visual representation of its classification accuracy, revealing the interplay between true positives, true negatives, false positives, and false negatives (Chicco et al., 2021).

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Figure : Confusion matrices of classification.

To counter the imbalance in our dataset, we opted for a binary approach, merging classes 0 and 1 to create a more balanced representation (Harangi et al., 2020). Therefore we got class 0 (“not successful”) with 45 (50.6%) and class 1 (“neutral”) with 44 (49.4%) representations. With this approach all algorithms, except RF and k-NN performed fair. GB performed the best, with moderate accuracy (0.59 averaged F1-score), as shown in Table 4 and Figure 4.

Table 4: Classification result of binary case.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classifier | Accuracy | Precision\_macro | Recall\_macro | F1\_macro |
| NB | 0.54 | 0.54 | 0.54 | 0.51 |
| k-NN | 0.5 | 0.49 | 0.5 | 0.49 |
| Decision Tree | 0.56 | 0.58 | 0.56 | 0.55 |
| LR | 0.54 | 0.54 | 0.54 | 0.53 |
| LDA | 0.55 | 0.55 | 0.55 | 0.54 |
| AdaBoost | 0.55 | 0.55 | 0.55 | 0.54 |
| GB | 0.59 | 0.59 | 0.59 | 0.59 |
| SVM | 0.58 | 0.59 | 0.58 | 0.56 |
| RF | 0.49 | 0.48 | 0.49 | 0.48 |

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Figure : Confusion matrices for binary case.

In addition, we conducted ML algorithms with a reduced set of predictor variables, as previously discussed. Specifically, we excluded all six variables related to the psychological profile of students within our sample. It is crucial to note that this exclusion did not substantially alter the performance across all the algorithms, as shown in Table 5 and Figure 5. The omission of psychological variables did not lead to a significant impact on the models, and they exhibited similar predictive accuracy. This underscores the robustness of the models even in the absence of these psychological variables in our predictive modeling framework.

Table 5: Classification results with selected features.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classifier | Accuracy | Precision\_macro | Recall\_macro | F1\_macro |
| NB | 0.34 | 0.4 | 0.38 | 0.28 |
| k-NN | 0.54 | 0.37 | 0.39 | 0.37 |
| Decision Tree | 0.54 | 0.42 | 0.41 | 0.41 |
| LR | 0.49 | 0.32 | 0.35 | 0.33 |
| LDA | 0.46 | 0.31 | 0.33 | 0.31 |
| AdaBoost | 0.37 | 0.28 | 0.39 | 0.31 |
| GB | 0.52 | 0.4 | 0.42 | 0.39 |
| SVM | 0.52 | 0.35 | 0.37 | 0.35 |
| RF | 0.52 | 0.36 | 0.36 | 0.34 |

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Figure : Confusion matrices with dropped variables regarding student psychological profile.

Given the suboptimal performance of our model, we employed t-SNE analysis to visually explore and comprehend the underlying patterns and relationships within the data, aiming to uncover potential complexities or overlaps that might have impacted the model's performance (Bibal et al., 2023). These analyses in two and three dimensions can be found in Figure 6 and Figure 7, respectively, and they show that the patterns in data may be hard to distinguish between, as was speculated. On the three- dimensional plot, it is however seen, that the separation between class 0 and class 1 can be found.

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Figure : 2D t-SNE plot.

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Figure : 3D t-SNE plot.

## Discussion

Research shows various small-group learning methods should be considered in teaching (S. Wang et al., 2023), as they promote academic achievement (Kalaian et al., 2018) as well as a positive attitude towards learning (Gaudet et al., 2010; Hillyard et al., 2010). In this regard, tandem learning (Stickler & Emke, 2011; G. Wilson & Blednick, 2011) is an easy-to-implement method. Not everyone responds well to a one-size-fits-all method, and therefore, uncovering insights for predictive model selection tailored to individual students or classrooms becomes imperative for teaching institutions. Customizing the approach to accommodate individual students or classrooms is crucial for educational institutions, as a uniform method may not resonate with everyone (Ahmad et al., 2021; Pratt, 2002). Extracting valuable insights from the educational dataset requires the application of data mining techniques. Given the potential complexity of the relationships between various factors, machine learning methods are considered the most appropriate (Hilbert et al., 2021).

In this study, we used nine ML algorithms, specifically (1) NB, (2) k-NN, (3) Decision Tree, (4) LR, (5) LDA, (6) AdaBoost, (7) GB, (8) SVM, and (9) RF to predict the success of tandem in three-states of tandem learning dataset comprising of 89 students with 14 variables in various (continuous, categorical and ordinal) forms. Models performed poorly to fairly. The best accuracy and F1 score were achieved when the target variable was transformed into two states, however, performance was still not the best. When taking variable importance into account, the model did also not notably improve. Best models of classification were not consistent, which emphasizes certain algorithms are more suited to a particular problem (Alzubi et al., 2018), as well as metric chosen for model evaluation (Erickson & Kitamura, 2021).

An important limitation of using ML in educational contexts is the issue of interpretability, particularly when employing complex models such as ensemble methods or support vector machines. These models often function as “black boxes,” offering limited insight into the decision-making processes behind their predictions. This poses a challenge in educational settings, where transparency is crucial for trust and practical application. Although we explored feature importance and t-SNE visualizations to aid interpretability, further work grounded in explainable AI (XAI) approaches is needed to ensure that such models can provide meaningful, actionable insights for educators and stakeholders. Damo raje v 2.3. poglavje?

While the study provides an initial exploration into the predictive modeling of tandem learning outcomes, the overall performance of the ML algorithms was limited—particularly in the three-class classification task. These modest results suggest that the available predictors, sample size, or the inherent complexity of student response patterns may not be fully captured by the models used. As such, the findings do not yet support strong conclusions regarding the applicability of tailored instructional strategies based on ML predictions. However, for the implementation of results, we would like for the models to be more accurate and consistent, therefore more insight regarding variables used is needed for model improvement. Based on the results of the present research, we suggest researchers to investigate the utilization of ML algorithms to measure the effectiveness of specific methodologies by applying different algorithms, which might perform very differently in different situations. Therefore, from the findings of the present research, we cannot state that there is a single ML method that should be preferred, nor that the description of the effectiveness of tandem learning might be described using the sole 13 predictors we employed in the present study. Nevertheless, the study highlights that some ML algorithms had fair accuracies, therefore their utilization for the assessment of pedagogical practices is encouraged.”

The application of supervised machine learning in predicting student response to tandem learning poses significant ethical challenges. While leveraging various general, psychological, and tandem learning-specific variables enhances predictive accuracy, it raises concerns regarding privacy, bias, and informed consent (Akgun & Greenhow, 2022; Starke et al., 2021). Collecting and analyzing personal data to predict individual behavior may compromise students' privacy, requiring strict adherence to data anonymization and consent protocols. Moreover, the inclusion of variables like cultural background or learning styles may inadvertently perpetuate biases or stereotypes (Marinucci et al., 2023). Transparency in model development, interpretability, and ongoing evaluation to mitigate biases remain pivotal.

## Conclusions and limitations

This study explores the use of machine learning algorithms to estimate whether students might respond positively to a specific instructional method—tandem learning—in mathematics education. While the application of AI in education holds promise, especially for personalizing teaching strategies, the findings of this study highlight the current limitations of such models in reliably predicting student outcomes. The modest performance of most algorithms suggests that either the available data or the nature of the learning context may not have been sufficient for strong predictive accuracy. Further research is required to identify the key features that drive successful model performance in this domain.

Importantly, the study does not assess whether tandem learning is effective overall, but rather focuses on predicting student responses based on a limited set of variables. Some potentially influential factors were not available, which may have introduced bias into the results. The relatively small sample size further constrains the generalizability of findings and may have impacted model stability. Additionally, class imbalance in the target variable—particularly the low proportion of students reporting unsuccessful experiences—may have skewed classification accuracy. Future studies should incorporate larger, more balanced datasets and a broader range of predictors to more robustly evaluate the utility of ML in modeling pedagogical outcomes.

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