# Influence of certain factors for tandem learning in mathematics

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## Abstract

### Background

The main objective of higher education institutions is to provide quality education to its students. One way to achieve this is is by introducing various teaching methods, one of which is tandem learning. 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. The knowledge is hidden among the educational data set and is extractable through data mining techniques. The primary objective of the study was to identify the key variables that significantly influence student performance in tandem learning using machine learning algorithms.

### Methods

A sample of N\_0 high school students and 13 predictor variables has been used. The outcome of interest was a three state variable indicating whether the student responded well to implementation of tandem learning into education environment or not. Study tested which predictor variables were most important using mutual information for all variables, for categorical variables and ANOVA for continuous variables.

### Results

The most important variables according to mutual information for predicting student response were

### Keywords

Assessment, education, tandem learning, data mining, teching methods

### Math subject classification, MSC2020

97D40, 97D60, 62P99

## Introduction and theoretical framework

### Teaching methods and tandem learning

Critic of frontal teaching and new theoretical didactics, psychological, pedagogic, sociologic findings and positive experience in practical work have lead to the development of new indirect forms of education process (Blažič et al., 2003). Based on strong research literatures various forms of small-group learning are effective in promoting greater academic achievement, more favorable attitudes toward learning, and increased persistence through SMET courses and programs (Roschelle et al., 2010).

Tandem learning is a special learning approach, where two students make an experiment together, formulate a report, solve a problem etc (Tomić 2002 Spremljanje pouka, Ljubljana: preveri se enkrat ali je direkt citat ali povzeto). It is a simple approach from organizational standpoint, as pair members have more chance for activity than in frontal teaching and group teaching, however they are not alone as in individual teaching method (Blažič et al., 2003). Simple diagram in figure Figure 1 depicts main components of group-learning relationship.

Figure 1: Relationships among interaction components of group learning (Slavin et al., 2003).A diagram of a group

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Figure : Relationships among interaction components of group learning (Slavin et al., 2003).

Many pedagogs, psychologists, sociologists and didactics say, that an individual in modern society is a member of many groups, so it is important, that students develop necessary social skills already in school. Imlementing group learning achieves five important goals (Peklaj, 2001): Students learn about eachother, group identity develops, students support each other, they learn to respect differences in between group members and students develop teamwork characteristics. This approach aligns closely with the five fundamental elements of cooperative learning outlined by (Johnson et al., 1991) (1) positive interdependence, where students rely on each other for success; (2) face-to-face promotive interaction, promoting constructive communication; (3) individual accountability and personal responsibility, ensuring each student's active participation; (4) the regular utilization of interpersonal and small group social skills; and (5) the consistent, periodic evaluation of group dynamics and performance. By embracing these principles, educators can better equip their students with the social and interpersonal competencies necessary for thriving in the modern world. (Slavin et al., 2003) identifies four considerable theoretical views on the achievement effects of cooperative learning, them being: motivationalist, social cohesion, cognitive-developmental and cognitive-elaboration, the latter two focusing on the interaction among groups of students. These four perspectives can be considered complementary. Syllabus of Slovene high schools (where the study will be conducted) mentions group work as one of the procedual skills? (Žakelj et al., 2008).

Group learning has its pros, as well as cons, summarized in table below:

|  |  |
| --- | --- |
| Pros | Cons |
| Better student performance (Puklek, 2001) | Group goal over individual goal (Puklek, 2001) |
| Mutual support and help development (Puklek, 2001) | Lack of experience leading to ressentiment of learning method (Puklek, 2001) |
| Different skills development (cognitive, emotional, motivational, social skills and understanding one-self) (Pateşan et al., 2016; Puklek, 2001) | Member focuses only on task given to him (Puklek, 2001) |
| Ekonomičnost – both from time management (leading individuals takes more time than leading a group) and financial (students can borrow books etc.) standpoints (Puklek, 2001) | Less effective due to member differences (Puklek, 2001) |
| Self esteem and respect increase (Pateşan et al., 2016) | Inequality regarding involved work (Puklek, 2001) |
| Less anxiety and stress (Goreyshi et al., 2013) | Difficult to perform in classes with large ammount of students (Kubale, 2015) |
| While some argue that cooperative learning might hinder high achievers by requiring them to explain material to lower-achieving peers, it's equally debatable that students who lecture their counterparts learn more than those who receive lectures. Nonetheless, most studies have shown equal benefits for high, average, and low achievers (Slavin et al., 2003). | |

Hundreds of studies have been conducted with main objective being being to determine the effects of cooperative learning on student achievement. We must keep in mind that this learning method is not only theoretical and a debate of research; it is used at some level by millions on teachers (Slavin et al., 2003). Many studies, which can be found in (Johnson & Johnson, 2011; Slavin, 1996; Webb, 1991) have found positive effect of for cooperative learning.

##### Variables that may impact group learning

In the quest to predict the effects of tandem learning on student performance, an array of variables must be considered to provide a comprehensive understanding of this dynamic educational approach. Examining the general factors, such as gender, class, professor, and previous grade, sheds light on the contextual background and baseline performance of students. Previous grade may not significantly impact tandem learning outcomes (Nunar, 2020; Slavin et al., 2003; Van Der Laan Smith & Spindle, 2007), while gender (Gnesdilow et al., 2013; Rodger et al., 2007) and class (Nunar, 2020) could exert a somewhat influential role.

Beyond these demographic aspects, the psychological dimensions of personality type, mathematical anxiety and motivation to learn mathematics come into play. Myers-Briggs Type Indicator (MBTI), which has become very popular in research world measures cognitive style in four dimensions: extroversion-introversion (EI), sensing-intuition (SN), thinking-feeling (TF) and judging-perceiving (JP) (Ramsay et al., 2000). Literature indicates that EI dimension is most important (Ramsay et al., 2000; Smith & Irey, 1974), while other MBTI dimensions are a subject of speculation and above all lack empirical literature (Ramsay et al., 2000). Mathematical anxiety negatively impacts performance in group work by corrupting working memory, affecting problem-solving and strategy selection, and causing an "affective drop" in high-stakes conditions (Klados et al., 2019), although its effects may be reduced in high interactivity conditions (Vallée-Tourangeau et al., 2013). This goes hand in hand with reserach showing that cooperative group work lessens math anxiety (Batton, 2010; Rafiei Taba Zavareh et al., 2022). Motivation – tu je ogromno člankov, kako skupinso delo vpliva na motivacijo, ampak skoraj nič v obratni smeri kar nas zares zanima?

Within the realm of tandem learning itself, variables like the quality and quantity of student interactions and whether a student outperforms their partner station all come into focus. (Puklek, 2001) emphasisez the positive role of competitiveness on student performance.

By synthesizing these diverse factors, we can develop a more holistic framework for predicting the effects of tandem learning on student performance and tailor educational strategies accordingly.

Razni viri, o kaksnih skupinah govorimo. Zakaj so mešani tipi dobri / slabi, enako spol.... Tomić 2003 da group size ne vpliva...

### 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. In contrast, machine learning, a subset of artificial intelligence, focuses on building predictive models by allowing computers to learn from data and make decisions or predictions. The sequences of steps identified in extracting knowledge from data is shown in Figure 2 below.

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Figure : Knowledge discovery process

### Connecting tandem learning and machine learning

Let us briefly discuss where AI is used in education today. We will focus mainly on the use of AI to support learning (student and teacher facing AI). Technologies can be considered in terms of whether they are mainly student teaching (with primarily instructionist approach), student supporting (primarily constructivist approach) or teacher supporting (which primarily help teachers do tasks they already do but faster or with less effort) (Holmes et al., 2019).

Beyond its broader applications, machine learning has been harnessed to predict student performance with remarkable precision. Leveraging the power of data analytics and advanced algorithms, machine learning models have been applied to forecast student success, identify at-risk learners, and tailor educational interventions. This transformative application of machine learning is exemplified by research conducted by (Siemens & Gasevic, 2012), which introduced the concept of "learning analytics" and demonstrated its potential in predicting student outcomes. Some other examples of predicting student performance with different metrics and models can be found in (Abana, 2019; Bhusal, 2021; Cortez & Silva, 2008; Kotsiantis et al., 2004; Minaei-Bidgoli et al., 2003). Aside from forecasting success, machine learning can help us identify most important variables that affect said forecast. In a landscape where multiple studies like (Hodges, 2018; Humphrey et al., 2009; Moradi et al., 2018; Scribner & Donaldson, 2001) have delved into the analysis of crucial features in learning environment, it becomes evident that only a scant few have harnessed the power of modern algorithms, such as machine learning, which hold the potential for significantly enhanced insights.

### Feature selection: theoretical background

The goal of feature selection is to select the smallest feature subset given a certain generalization error, or alternatively finding the best feature subset with k features, that yields the minimum generalization error. We are reducing data structure complexity in order to identify important feature variables as a set of new training instances (Huang et al., 2014). Additional objectives of feature selection are as follows: (i) improve the generalization performance with respect to the model built using the whole set of features, (ii) provide a more robust generalization and a faster response with unseen data, and (iii) achieve a better and simpler understanding of the process that generates the data.(Vergara & Estévez, 2014).

Feature selection methods are typically categorized into three primary groups: wrappers, embedded methods, and filter methods (Guyon & Elisseeff, 2003).

Wrappers involve the incorporation of an inductive learning algorithm as part of the process of evaluating different feature subsets (Kohavi & John, 1997). These methods commonly assess performance based on the classification rate achieved on a testing set. While wrappers may indeed yield strong generalization results, they come with the notable drawback of substantial computational demands, especially when applied to high-dimensional datasets. Furthermore, they are susceptible to issues such as overlearning and sensitivity to initialization, which can limit their practicality.

Embedded methods take a different approach by integrating knowledge about the specific structure of the class of functions employed by a given learning machine (Lal et al., 2006). Embedded methods, in comparison to wrappers, tend to be less computationally intensive. However, they remain considerably slower than filter methods and are often intertwined with the characteristics of the learning machine, thus making the selected features contingent on the specific algorithm employed.

Filter methods operate on the premise of total independence between the learning machine and the data, utilizing a metric that is agnostic to the induction learning algorithm for the assessment of feature subsets (Wlodzislaw et al., 2003). Filter methods, unlike wrappers, exhibit a degree of robustness against overfitting. However, they may not consistently identify the most optimal feature subset for classification or regression tasks, potentially leading to suboptimal results.

Each of these three feature selection methods comes with its own set of advantages and limitations, and the choice of which to employ in a given context should be guided by the specific requirements and constraints of the problem at hand. (Guyon & Elisseeff, 2003; Vergara & Estévez, 2014).

Feature extraction, conversely, entails reducing the dimensionality of data by consolidating correlated features into synthetic ones, while retaining the fundamental characteristics of the original features (Anowar et al., 2021). That comes with several benefits including – Improvement of MLAs’ performance through less misleading and redundant features. – Avoidance of overfitting through fewer features, and therefore lesser assumptions by the model, and simpler the model. – Less computing time and much less storage is required with lower data dimensions. – More ease of data visualization and interpretation (Khalid et al., 2014).

## Empirical work

## Methodology

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

## Sample

The sample was comprised of N students from 11th and 12th grade of a Slovenian Gymnasium (i.e., high school).

## Procedure

After obtaining students’ (or their parents’, if the students were minors) signed informed consent and the school principals’ approval, we collected and examined the success of tandem learning in regards to several variables. Success (overall regarding both learning and diversification of class) was measured in 3 states (good, neutral and bad). Independent variables were in general sense (gender, class, professor, previous grade) in psychological sense (MBTI variables: extroversion-introversion, sensing-intuition, thinking-feeling and judging-perceiving and other variables: mathematical anxiety and motivation) and in regards to tandem learning (qualitytive interaction, quantitativy interaction and whether student performed more than their partner). Data was anonymized using a coding scheme, such that anonymity and objectiveness were assured in every step of the research. The collected data were accessible only to the researcher.

Data was collected following after students included in research were involved in tandem learning environment during the course of approximately one week. A portion of the class period was devoted to normal classroom work, while some portion of the class period was devoted to working in tadem. Randomization was not taken into consideration. Students were assigned into pairs in regards to their partner at the two seat desk.

The authors declare that all participants (and their parents, in case they were minors) gave their informed consent. All participants took part on a voluntary basis and were not financially remunerated for their participation in the research. The study was carried out following the ethical standards of the 1964 Declaration of Helsinki and the European data protection law (European General Data Protection Regulation–GDPR UE 2016/67).

For personality variables, we utilized MBTI test, specifically the Open Extended Jungian Type Scales (OEJTS) as a cost-effective alternative. The OEJTS was designed as an open-source alternative to the widely recognized Myers-Briggs Type Indicator (MBTI). Data was gathered from (*Fastest Myers-Briggs Test*, n.d.), which is based on (*Myers-Briggs/Jung Test: Open Extended Jungian Type Scales*, n.d.) both of which being available for public use like this under creative commons. MBTI test has both arguments for (Carlson, 1985; Carlyn, 1977; Randall et al., 2017) and against (Boyle, 1995; Coan, 1978; Druckman & Bjork, 1991) it. It’s validity and reliability must be taken into account as precaution ...Test to determine motivation was gathered from (Sundre et al., 2012), while mathematical anxiety (AMAS test) was gathered from (*PsyToolkit*, n.d.). AMAS and motivation tests have been proven to be reliable, valid and effective in educational context (Fiorella et al., 2021; Hopko et al., 2003; Sundre et al., 2012; Yavuz et al., 2012). All the variables above were accounted as continuous variable, rather than categorical (e.g. IE score of “26” rather than “extrovert”), to prevent assumption of bipolarization of people (Ramsay et al., 2000). That can also lead to better model accuracy (Carlson, 1985; Carlyn, 1977; DeVito, 1985).

## Data analysis

The gathered data was analysed using Python programming language, primarily using pandas and scikit-learn libraries (scikit version 1.3.2). Raw anonymized dataset with statistics code is openly accessible on [GitHub](https://github.com/borbregant/ai_tandem_learning).

In suma, we modified all data in the form of tidy data. This was later transformed into integer type using label encoding. ... data (normally distributed) were scaled, as this provides better insight to feature importance (citat). ... were evaluated using mutual information, ... using chi^2 , .... using ANOVA.

## Results

### Student sample

Statističen opis kakšen je bil vzorec (intervali zaupanja za npr. cilnje spremenljivke, …). MBTI vzamemo zvezne spremenljivke, ki normalizira podatke, ki bi sicer implicirali bipolarnost ljudi. (Ramsay).

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### Variable importance

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A diagram of different colored squares

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Table : Related feature variables

|  |  |  |
| --- | --- | --- |
| Variable | Possible values | Variable type |
| Gender | 0-1 (Male, female) | A priori state |
| Class | 0-6 (7 present classes) | A priori state |
| Teacher | 0-3 (4 teachers) | A priori state |
| Previous grade | 1-5 | A priori state |
| Extroversion score | 0-1 (extrovert – introvert) | Psychological background |
| Sensing / intuition | 0-1 | Psychological background |
| Thinking / feeling | 0-1 | Psychological background |
| Judging / perceiving | 0-1 | Psychological background |
| Mathematical anxiety | 7-45 | Psychological background |
| Motivation | 9-35 | Psychological background |
| Qualitative interaction | 1-3 (little communication – lots of communication) | Tandem learning |
| Quantitative interaction | 1-3 (work was not productive – work was productive) | Tandem learning |
| Outperforming partner | 1-3 (worked less – outperform) | Tandem learning |

Table : Head of dataset

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Performance | Gender | Class | Teacher | Extroversion score | ... | Teacher presence |
|  | M | 3B |  | 86 |  |  |
|  | F | 3B |  | 76 |  |  |
|  |  |  |  |  |  |  |

## Discussion

In this case study, we used ... feature extraction algorithms.

## Conclusions and limitations

This study demonstrates that ... variables are most important for predicting success of tandem learning among Slovene high school students. The key factors that influence success have been identified which can assists both teachers and students of mathematics. The potential incorporation of gathered information needs to be investigated further. However, some authors have suggested that students should not be forced to use learning approaches that do not suit their cognitive style. Če ugotovimo, da ni natančen model je v ramsay špekulacije za mbti zakaj bi katera lahko vplivala

Study does not include a prediction whether tandem learning is overall effective or not. It simply includes which variables impact student response. Dimensionality reduction techniques were also not taken into account, as with our study it is not necessary. Some of the variables that are likely relevant for group learning like ... were also not taken into account as .... The dataset was also slightly unbalanced as ... We also did not include how group composition (different gender, personalities ,...)

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