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Factors Influencing Tandem Learning in Mathematics

Bor Bregant
Universitiy of Primorska, Faculty of Education, Koper, Slovenia, *98233001@student.upr.si*

Daniel Doz
Universitiy of Primorska, Faculty of Education, Koper, Slovenia, *daniel.doz@pef.upr.si*

Sanela Hudovernik
Universitiy of Primorska, Faculty of Education, Koper, Slovenia, *sanela.hudovernik@pef.upr.si*

The main objective of secondary education institutions is to provide quality education to its students. One way to achieve this is by introducing various teaching methods, one of which is tandem learning, which is a small-group cooperative learning 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. The knowledge is embedded in the educational data set and is extractable through data mining techniques. The primary objective of the study was to identify the key factors that significantly influence student outcomes (including both emotional well-being and knowledge improvement) in tandem learning using machine learning algorithms. The study was conducted in a mathematics class during the course of one week of tandem learning implementation in the school year 2023/24 with a sample of 89 high school students from a selected Slovene high school and 13 predictor variables (gender, class, teacher, recent mathematics grade, MBTI variables, mathematical anxiety, motivation, qualitative interaction, quantitative interaction, and whether the student outperformed their partner). The outcome of interest was a three-state dependent variable indicating whether the student responded well to the implementation of tandem learning into the education environment. The present study tested which predictor variables were most important using mutual information and recursive feature elimination for all variables. The most important factors according to mutual information for predicting student response were outperforming the partner, class, and qualitative interaction within the tandem and according to recursive feature analysis qualitative interaction, outperforming partner and gender.

Keywords: secondary education, mathematics, tandem learning, data mining, organizational forms of learning

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INTRODUCTION

When teaching mathematics, ensuring that students comprehend the topics deeply and retain knowledge is of paramount importance (Adler et al., 2014). Several educational models have recently suggested that students should also learn through indirect forms of educational processes (Arias & Peralta, 2011). In particular, research has shown that the effectiveness of mathematics learning diminishes in large classrooms (Mbofana & Banda, 2022; Olasen & Lawal, 2020) and with a traditional, teacher-centered method (Dervić et al., 2018; Lasry et al., 2014). While this approach allows teachers to have control over the learning process, it may lead to ineffective learning. Therefore, the literature has suggested considering various forms of small-group learning (Kim & Kim, 2021; Wang et al., 2023). The advantages of these learning models include promoting greater academic achievement (Kalaian & Kasim, 2014), fostering more favorable attitudes towards learning (Gaudet et al., 2010; Hillyard et al., 2010), as well as increasing participation in several STEM courses and programs (Kalaian et al., 2018; Wieselmann et al., 2020).

Tandem learning can be considered a form of small-group learning, where two students collaborate on experiments, formulate reports, solve problems, or engage in similar activities (Stickler & Emke, 2011; Wilson & Blednick, 2011). This approach has the potential to increase students' activity levels (Blažič et al., 2003). However, despite the positive aspects of implementing tandem learning, several factors may impact its effectiveness. Researching factors that impact tandem learning effectiveness is crucial for understanding its potential benefits and limitations, as well as for predicting its effectiveness in different contexts, thereby informing decision-making in educational settings. General-demographic factors (e.g., gender), psychological factors (e.g. personality type) and other tandem-related-factors (e.g. quality of the interaction within the tandem) could influence the outcomes in tandem learning.

Although the topic is important, especially in providing educators with insights into predicting the effectiveness of adopting this learning model, the literature on it is still scarce. Additionally, due to the complexity of the relationships between the factors, classical statistical methods may not be deemed suitable for analyzing the impact of the aforementioned factors on the effectiveness of adopting tandem learning or predicting its efficacy.

Therefore, to provide educators with clear information about the effectiveness of using tandem learning in specific educational contexts and to explore the extent to which several factors impact the adoption of tandem learning, the present paper examines the role of the aforementioned factors using machine learning techniques. These techniques are deemed to be more robust when analyzing variables with complex interconnections and relationships (Hilbert et al., 2021; Ho et al., 2021).

The use of machine learning methods to predict students' achievements or outcomes in education is not entirely new (Ho et al., 2021; Ibarra-Vazquez et al., 2023; Luan & Tsai, 2021; Yağcı, 2022). However, to the best of our knowledge, no research has investigated the factors involved in predicting the effectiveness of tandem learning using machine learning algorithms. The purpose of this research is to examine and interpret the effects of several general-demographic factors, psychological factors, and tandem-related factors, specifically gender, class, teacher, recent mathematics grade, MBTI variables, mathematical anxiety, motivation, qualitative interaction, quantitative interaction, and whether the student outperformed their partner.

Theoretical Framework

Tandem Learning

Critiques of frontal teaching and new theoretical didactics, psychological, pedagogic, and sociological findings, and positive experience in practical work have led to the development of new indirect forms of education processes (Arias & Peralta, 2011). Concerning the new education practices that have emerged, several researchers have suggested adopting various forms of small-group learning (Kim & Kim, 2021; S. Wang et al., 2023), since they are more effective in promoting greater academic achievement (Kalaian & Kasim, 2014), more favorable attituded towards learning (Gaudet et al., 2010; Hillyard et al., 2010), and increased persistence through STEM courses and programs (Kalaian et al., 2018; Wieselmann et al., 2020). Research in mathematics education has shown the effectiveness of working in small groups as well, especially concerning academic achievements (Bonesrønning et al., 2022; Ridwan & Hadi, 2022) and a deeper understanding of mathematics topics (Wester, 2021). In particular, working in small groups might also help students to increase their motivation towards learning mathematics (Begeny et al., 2020; In'am & Sutrisno, 2021).

Many pedagogues, psychologists, sociologists, and education theoreticians state, 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 (Johns et al., 2017; Selimović et al., 2018). Implementing group learning achieves five important goals (Peklaj, 2001): (1) students learn about each other, (2) they develop group identity, (3) students support each other, (4) they learn to respect differences between various group members, and (5) students develop teamwork characteristics. This approach aligns closely with the five fundamental elements of cooperative learning outlined by Johnson et al. (1991), i.e. (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.

Group learning has its pros, as well as cons, summarized in

Table 1

Table 1
The pros and cons of group learning

Pros	Cons
Better student performance (Hobri et al., 2018; Rabgay, 2018).	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) (Puklek, 2001).	Member focuses only on the task given to him (Puklek, 2001).
Economical perspective – 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 (Ghufron & Ermawati, 2018).	Difficult to perform in classes with a large amount of students (Kubale, 2015).

In contrast to traditional group learning approaches where individuals work together toward a common goal, cooperative learning emphasizes collaborative efforts among participants to achieve mutual success and promote social and relational skills within the classroom (Bores-García et al., 2021). Cooperative learning entails more than just working in groups; it involves active engagement, shared responsibilities, and interdependence among learners (Yang, 2023).

Among the small-group cooperative learning practices, tandem learning should be mentioned. It is a special learning approach, where two students make an experiment together, formulate a report, solve a problem, etc. (Stickler & Emke, 2011; Wilson & Blednick, 2011). It is a simple approach from an organizational standpoint, as pair members have more chance for activity than in frontal teaching and group teaching, however, they are not alone as in the individual teaching method (Blažič et al., 2003).

By situating tandem learning within the cooperative learning framework, we recognize its alignment with collaborative pedagogy. Despite its dyadic nature, tandem learning shares the principles of cooperative learning. In this article, we will sometimes interchange the terms “cooperative” and “tandem” to reflect the collaborative nature of tandem learning within the broader framework of cooperative learning practices. This flexibility in terminology allows us to integrate tandem learning seamlessly into discussions surrounding cooperative learning methodologies. By recognizing tandem learning as a form of cooperative learning, we enhance our understanding of collaborative methodologies, particularly within small-group settings where much research has been concentrated (i.e., meta-analyses, see Ridwan & Hadi, 2022; Wiese et al., 2022). This acknowledgment underscores the significance of tandem learning within the broader discourse on effective educational strategies.

Factors Influencing Tandem Learning

With the aim of predicting the effects of tandem learning on student outcomes, 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, teacher, and previous grade, sheds light on the contextual background and baseline performance of students (Azina & Halimah, 2012; Ma & Klinger, 2000). The variable "Previous grades" may not significantly impact tandem learning outcomes (Van Der Laan Smith & Spindle, 2007), while gender (Rodger et al., 2007) could exert a somewhat influential role. Data on how teachers and belonging to specific classes impact group learning is scarce, aside from general instructions for teachers on how the said method should be implemented (Van Diggele et al., 2020). Literature has not examined yet the impact of teachers and belongingness to specific classes on the efficacy of implementing tandem learning. No specific hypotheses can therefore emerge, however, it might be speculated that students from different classes and studying with different teacher might react very differently to the effectiveness of tandem learning.

Beyond these demographic aspects, the psychological dimensions of personality type (Akben-Selcuk, 2017; Kurniawati et al., 2023; Peklaj et al., 2015), math anxiety (Li et al., 2021), and motivation to learn mathematics (Tella, 2007) might have an important role in predicting the effectiveness of small-group learning of mathematics. Consequently, it can be hypothesized that students experiencing higher levels of mathematics anxiety and/or lower motivation to learn may perceive tandem learning as less effective compared to students with lower levels of math anxiety and/or higher motivation. Additionally, more introverted or shy students might feel increased nervousness when working in pairs, potentially leading them to evaluate their tandem learning experience less favorably than their more extroverted or open peers.

Concerning students' personality type, the *Myers-Briggs Type Indicator* (MBTI), which has become very popular in research, measures cognitive styles in four dimensions: extroversion-introversion (EI), sensing-intuition (SN), thinking-feeling (TF), and judging-perceiving (JP) (Ramsay et al., 2000). Literature indicates that the EI dimension is the most important predictor regarding cooperative learning (Farooqi, 2021; Ramsay et al., 2000), while the other MBTI dimensions are subject of speculation and, above all, lack empirical literature (Ramsay et al., 2000).

Math anxiety (MA) 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 is corroborated by research showing that cooperative group work lowers mathematics anxiety (Rafiei Taba Zavareh et al., 2022). Mathematical motivation is a factor negatively correlated to MA (Bregant et al., 2024). Collaborative learning activities have been conceived as a source of influence on individual motivation (Järvelä et al., 2010). Additionally, research has shown that MA is closely related to gender, as girls generally experience higher levels of mathematics anxiety (Wang et al., 2020).

Explaining why this phenomenon occurs does not find a unique and uncontroversial answer in the literature; however, it is believed that gender stereotypes, i.e., false beliefs that mathematics is more of a "male" domain, might play a non-negligible role in explaining this relationship (Rossi et al., 2022).

Within the realm of tandem learning itself, variables like the quality and quantity of student interactions and whether a student outperforms their partner station should be considered as well. Given the limited research on variables within the realm of tandem learning, it is crucial to investigate their dynamics and their impact on the outcomes of tandem learning. Such research is essential for informing effective pedagogical practices. Small-group learning in mathematics is linked to task-related verbal interaction (Webb, 1991) and promotes intersubjectivity and circular, self-referential learning (Cobb et al., 1992). Additionally, Puklek (2001) emphasizes the positive role of competitiveness on student performance.

By synthesizing these diverse factors and exploring their impact on small-group learning, we can develop a more holistic framework for predicting the effects of tandem learning on student performance and tailor educational strategies accordingly. Based on the abovementioned literature, it is impossible to establish which factor might have the greatest impact on students' opinions about the effectiveness of tandem learning in mathematics. Therefore, an exploratory study is proposed.

Machine Learning In Education

Machine learning (ML) applications in education have become increasingly prevalent, providing valuable tools for predictions and data analysis that contribute to informed decision-making (Ciolacu et al., 2017; Kuleto et al., 2021; Luan & Tsai, 2021). One prominent area is educational predictions, where machine learning algorithms leverage student data to forecast outcomes such as academic performance (Balaji et al., 2021) and graduation rates (Moscoso-Zea et al., 2019). These predictive models often integrate diverse features, including demographic information, past academic performance, attendance records, and engagement levels (Issah et al., 2023). By analyzing these features, machine learning algorithms can identify patterns and correlations that enable educators and administrators to intervene early and implement targeted interventions for students at risk (Al-Shabandar et al., 2019) and/or implement the so-called "precision education" (Luan & Tsai, 2021; Tsai et al., 2020; Yang et al., 2021), that tailors instruction, content, and pacing to the individual needs, interests, and abilities of each student.

Feature importance plays a crucial role in these machine learning applications, determining which variables contribute most significantly to the predictive or analytical models (cf. Sobnath et al., 2020). Evaluating feature importance is vital for understanding the factors that influence educational outcomes. Commonly used methods include Mutual Information (MI) and Recursive Feature Elimination (RFE). MI measures the information shared between features and the target variable, helping identify the most informative variables without assuming linear relationships (Beraha et al., 2019; Doquire & Verleysen, 2012). RFE, on the other hand, systematically removes less important features, providing a ranking that highlights the most impactful ones, and reducing overfitting (Darst et al., 2018). MI is non-parametric, while RFE depends on the specific model used during the elimination process. These methods contribute to model interpretability, allowing educators and policymakers to focus on key variables influencing educational predictions or data analysis.

METHOD

Investigating tandem learning involves understanding the diverse elements that impact this collaborative approach. As presented above, several factors might have a non-negligible impact on the efficacy of this learning method. Therefore, the aim of the present research is to explore how various variables interact (independent variables i.e. gender, class, teacher, recent mathematics grade, MBTI variables, mathematical anxiety, motivation, qualitative interaction, quantitative interaction, and whether the student outperformed their partner) within tandem learning setups to enhance overall educational effectiveness (dependent variable). The research problem revolves around exploring the complexities of these interactions to optimize tandem learning experiences for a broad spectrum of learners.

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

The main hypothesis is therefore the following:

H: Variables regarding tandem learning itself (qualitative interaction, quantitative interaction, and whether the student outperformed their partner) have a greater impact on the efficacy of this method than general (gender, class, teacher, recent mathematics grade) and personality variables (MBTI variables, mathematical anxiety, motivation).

Sample

The sample was comprised of 44 (16 boys and 28 girls) grade 11 (approx. 16 years old) and 45 (12 boys and 33 girls) grade 12 (approx. 17 years old) for a total of 89 students of a Slovenian Gymnasium (i.e., high school). Access to the school records for providing students' socio-economic status (SES) was not granted. The sample was drawn from a population of approximately 300 grade-11 and grade-12 students attending a selected Slovenian Gymnasium. This sample is a convenience sample, consisting of students who were accessible and willing to participate in the study as directed by the school's principal. No specific exclusion criteria were applied in this selection process.

Procedure

After obtaining students’ informed consent and the school principals’ (where the case study was conducted) approval, we collected and examined the success of tandem learning in regard to several variables. The dependent variable (also called outcome of interest or target variable) was labeled “Successsulness” (overall regarding both learning and diversification of class) and it was measured in three states: (1) good, (2) neutral, and (3) bad. Independent variables (also called features, factors or predictor variables) were (1) general-demographic (gender, class, teacher, and the mathematics grade achieved in the most recent academic year), (2) psychological (MBTI variables:

extroversion-introversion, sensing-intuition, thinking-feeling, and judging-perceiving, and other variables: mathematical anxiety and motivation), and (3) tandem-learning-related (qualitative interaction, quantitative interaction, and whether student outperformed their partner). Data was anonymized using a coding scheme, such that anonymity and objectivity were assured at every step of the research. The collected data were accessible only to the researcher.

Data was collected after participants were involved in a 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 tandem – purely by teacher's judgment (e.g. in the 45-minute class period, 20 minutes are for frontal teaching, while time remaining is devoted to tandem learning). Randomization was not taken into consideration, as it commonly occurs in pedagogical research (Robson & Huckfeldt, 2012). Students were assigned into pairs regarding their partner at the two-seat desk.

All participants gave their informed consent. Also, 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, the European data protection law (European General Data Protection Regulation – GDPR UE 2016/67), and the European Code of Conduct for Research Integrity.

Instruments

For personality variables, the MBTI test was utilized, 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 MBTI. Data was gathered from the *Myers-Briggs/Jung Test: Open Extended Jungian Type Scales* (n.d.), which was available for public use under Creative Commons. The MBTI test has both arguments for (Carlson, 1985; Randall et al., 2017) and against it (cf. Boyle, 1995; Druckman & Bjork, 1991). Its main drawback is the lack of the stability-neuroticism trait (Cerkez et al., 2021). Other limitations include: (1) no indication of one's values and motivations, (2) it does not measure how well the preferred functions are performed, and (3) it is a forced choice instrument (Coe, 1992). The instrument is generally considered valid and reliable (Mawhinney & Lederer, 1988; Wheeler, 2001).

The *OEJTS* has four personality types, which can combine up to 16 types (Mawhinney & Lederer, 1988): Introversion-Extroversion; Sensing-Intuition; Feeling-Thinking; and Judging-Perceiving. The instrument has 60 items, divided into two sections. In the first section, participants indicate their position between two opposing personality descriptions (e.g., "skeptical – wants to believe"). In the second part of the test, participants indicate on a 5-point Likert scale their agreement with statements (e.g., "I will admit to being wrong in order to learn the truth"). We opted for choosing only the first section of the instrument, comprised of 32 items, to shorten the instrument.

The *Abbreviated Math Anxiety Scale* (AMAS; Hopko et al., 2003) was used to measure students' math anxiety levels. This scale contains nine 5-point Likert-type items related to two aspects of MA, i.e. five items related to learning math anxiety, and four items related to math evaluation anxiety. The instrument was translated into Slovenian by the authors using the forward-translation method: authors worked independently on the translation of the instrument and then compared the translations with the purpose of assessing equivalence. The final version was reviewed by a group of three independent researchers in the field of mathematics education.

The *Attitudes Toward Math Instruction* (ATMI; Tapia & Marsh, 2004), initially comprised 40 items categorized into four subscales: self-confidence (15 items), the value of mathematics (10 items), enjoyment of mathematics (10 items), and motivation to learn mathematics (5 items) was used to measure student’s attitude toward mathematics and motivation toward mathematics (MM). In our study, we adapted the instrument and focused specifically on the motivation to learn mathematics, utilizing a subset of 7 items, consistent with the approach taken by Sundre et al., (2012). Participants were asked to rate their agreement with each statement on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This modification allowed for a streamlined assessment while maintaining alignment with the original ATMI framework.

Both the AMAS and ATMI tests have been proven to be reliable, valid, and effective in educational contexts (Fiorella et al., 2021; Hopko et al., 2003; Primi et al., 2020; Sundre et al., 2012).

In pursuit of internal consistency, the Cronbach’s alpha coefficient was used for each subscale (see Table 2). Anxiety and motivation tests’ internal consistency were good. On the other hand, MBTI dimensions can be a subject of debate. In our sample, internal consistency for introversion and judging dimensions were acceptable, while the feeling dimension was poor and the sensing dimension was unacceptable. Results are comparable to those found in previous works (Boyle, 1995).

Table 2
Internal consistency test using Cronbach’s alpha

Instrument	Number of items (question)	Cronbach α	95% confidence interval
AMAS	9	0.77	[0.68, 0.83]
ATMI - motivation	7	0.87	[0.83, 0.91]
Introversion	8	0.69	[0.58, 0.78]
Sensing	8	0.47	[0.28, 0.62]
Feeling	8	0.54	[0.39, 0.68]
Judging	8	0.71	[0.60, 0.79]

All the abovementioned variables were accounted as continuous variables, rather than categorical (e.g. IE score of “26” rather than “extrovert”) as the shift towards employing continuous scales aims to mitigate the polarizing effect often associated with categorical classifications (Ramsay et al., 2000). That can also lead to better model accuracy (Carlson, 1985). The survey utilized established elements with slight adaptations to accommodate diverse cultural and social contexts while keeping the instrument constructs consistent.

Fifty-six diverse questions were assessed and condensed into 14 variables, one of which (outcome of interest, also called target or dependent variable) was a three-state variable capturing student preferences toward the method (labeled “Successfulness”), rated on a Likert scale. Three predictor variables (also called feature variables or factors) were categorical in nature, while others were numeric, but treated as continuous.

Data Analysis

The gathered data was analyzed using Python programming language, primarily using *pandas* (version 3.11.4) and *scikit-learn* (version 1.3.2) libraries. Raw anonymized datasets with statistics codes are openly accessible (Bregant, 2023).

All data was modified in the form of tidy data (Wickham, 2014). Label encoding was used to tackle categorical variables (Gender, Teacher, and Class). Questions regarding personality type, motivation, and anxiety were determined into fitting values within the specified coding framework (Hopko et al., 2003; *Myers-Briggs/Jung Test: Open Extended Jungian Type Scales*, n.d.; Sundre et al., 2012).

To determine which factor impacts the most the effectiveness of tandem learning, machine learning techniques have been used. To substantiate the hypothesis on feature importance, we employed mutual information (MI) and recursive feature elimination (RFE) with regard to logistic regression methodologies (Convy et al., 2022), chosen for their capability to effectively handle a blend of both continuous and categorical data (Liou et al., 2023), ensuring a robust validation process (Cellucci et al., 2005).

MI and RFE values in the present study are used to identify the importance of different variables in the context of tandem learning. The lower the RFE rank, and higher the MI value, the more important the variable was deemed.

Feature variables tested, together with their possible values and type can be found in Table 3.

Table 3
Related feature variables

Variable	Possible values	Variable subtype
Gender	0-1 (Male, female)	General-demographic
Class	0-6 (7 present classes)	General-demographic
Teacher	0-3 (4 teachers)	General-demographic
Previous grade	1-5	General-demographic
Introversion / extroversion	8-40, 24 being “neutral” point	Psychological background
Sensing / intuition	8-40, 24 being “neutral” point	Psychological background
Thinking / feeling	8-40, 24 being “neutral” point	Psychological background
Judging / perceiving	8-40, 24 being “neutral” point	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 – outperformed)	Tandem learning

FINDINGS

Preliminary analysis

The dataset description with quantile information is summarized in Table 4 and Table 5. We can observe that "Successfulness" (target variable) is averaged higher than all variables regarding tandem learning itself. Additionally, all variables regarding the MBTI cognitive style of students are evenly split between categories, except that subjects were mostly introverted.

Table 4
Dataset description of target variable (dependent variable i.e. Successfulness) and feature variables regarding general-demographic subtype and tandem learning itself with quantile information

	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			

Table 5
Dataset description of feature variables regarding psychological background with quantile information

	AMAS	ATMI - 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

The distributions of the target and predictor variables can be found in Figure 1. We employed the Shapiro-Wilk (SW) test to assess the normality of certain variables, although this step was not essential as our selected methodologies, specifically MI and RFE (with logistic regression) did not require normally distributed inputs. Additionally, certain variables within our dataset were inherently categorical, as predetermined before analysis, further mitigating the necessity for normality assumptions in our feature modeling (Rado et al., 2019; Tavazzi et al., 2020).

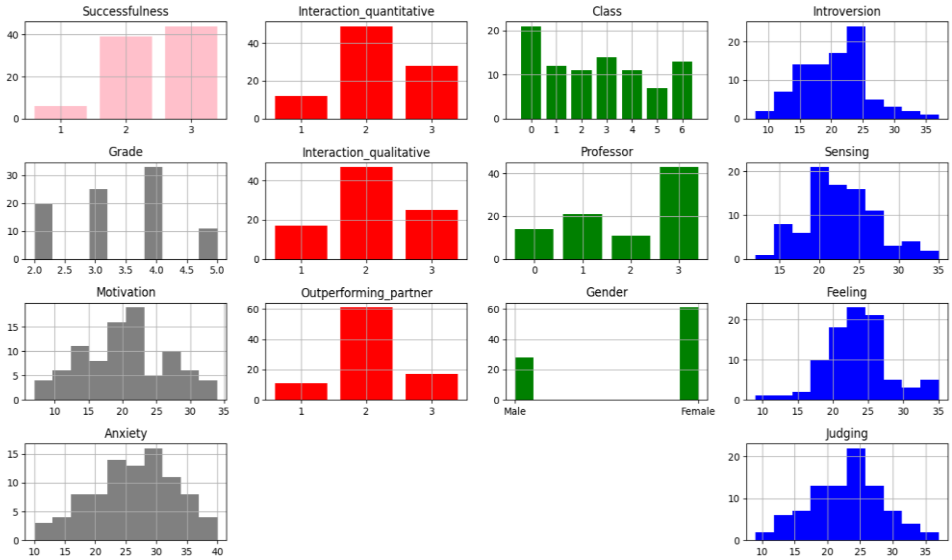

Figure 1
Histograms of target (pink) and feature variables

Variable importance

The list of feature importances including their MI and RFE scores are given in Table 6 and visualized in Figure 2 and Figure 3. From Table 6 it might be understood that the variable with the greatest MI was ‘Outperforming the partner’ (MI = .22), with an RFE ranking of 1. This means that students’ opinions about the fact they can outperform their partner is the greatest predictor of the efficacy of tandem learning. Similarly, the qualitative interaction variable had an RFE ranking of 1 and a quite high MI (.08). This suggests that the quality of interaction, such as the depth of discussion, engagement, and mutual understanding between partners, plays a crucial role in determining the success of tandem learning, underscoring the importance of not only the individual skills and attitudes of learners but also the dynamics of their collaborative efforts in achieving learning outcomes. Note that the variables were only ranked in order and not selected whether they were significant or not. Some disparities emerged, yet the overarching insights remained consistent. For instance, while specific rankings varied, the greater scheme was consistent as variables were grouped (clustered) regarding tandem learning, psychological profile, and general-demographic, as established in Table 3. Despite, as shown, internal consistency and the importance factor for some variables were not optimal, we still chose to include them, as they might still have predictive power or be significantly related to the target variable (Chen et al., 2020). This decision was balanced, as our dataset was not small, therefore overfitting was not a primary concern (Ying, 2019). Trade with model interpretability was taken into account. As was hypothesized, variables regarding tandem learning itself held the most importance, especially qualitative interaction and outperforming partners.

Table 6
Feature importances using MI and RFE

Variable	Mutual information	RFE ranking
Outperforming_partner	0.22	1
Class	0.09	5
Interaction_qualitative	0.08	1
Teacher	0.04	3
Anxiety	0.01	8
Gender	0.01	1
Grade	0.00	4
Interaction_quantitative	0.00	2
Motivation	0.00	11
Introversion	0.00	10
Sensing	0.00	6
Feeling	0.00	7
Judging	0.00	9

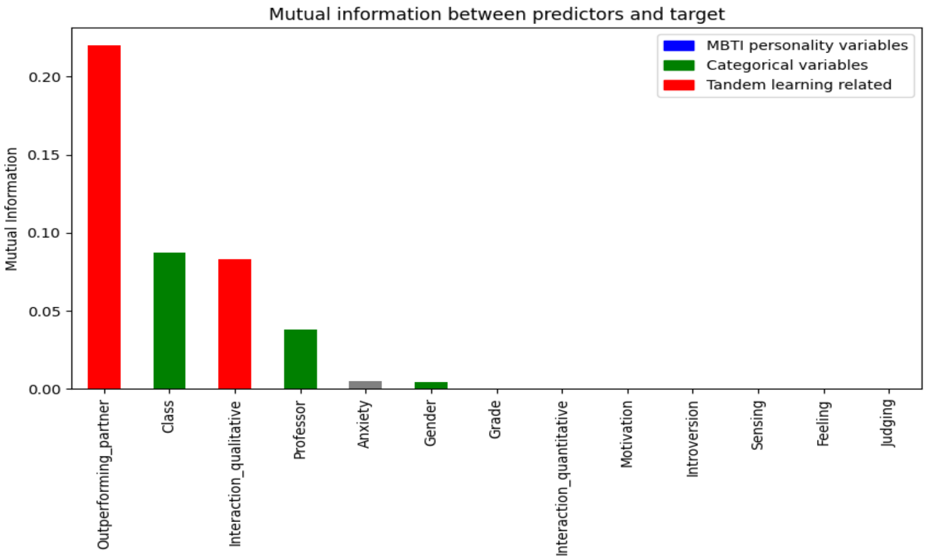

Figure 2
Mutual information between predictors and target

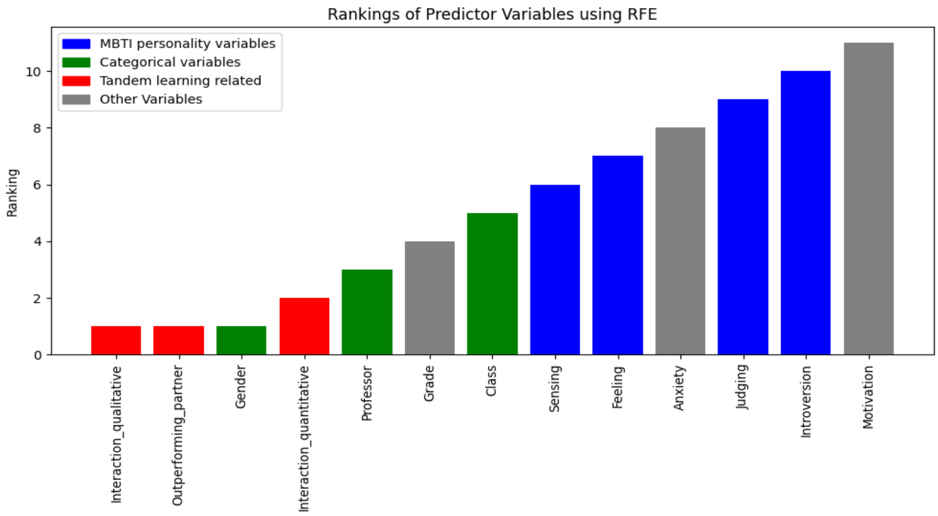

Figure 3
Rankings of predictor variables using RFE

DISCUSSION

Literature has emphasized the important role of small-group learning (Wang et al., 2023) since it leads to higher academic performances (Hobri et al., 2018; Kalaian & Kasim, 2014; Rabgay, 2018) and it promotes more positive attitudes toward learning (Gaudet et al., 2010; Hillyard et al., 2010). Among such learning models, tandem learning should be mentioned (Stickler & Emke, 2011; Wilson & Blednick, 2011), which promotes students' activity (Blažič et al., 2003). However, several factors might influence the effectiveness of tandem learning. Therefore, the present research aimed to investigate the various elements influencing tandem learning, particularly focusing on the factors that contribute to the success of this collaborative approach. The central hypothesis proposed that variables related to tandem learning itself i.e. quality and quantity of the tandem interaction, as well as whether the student outperformed their partner would have a more significant impact than general and personality variables. Since the relationship between these factors may be complex, machine-learning methods are deemed the most suitable (Hilbert et al., 2021; Ho et al., 2021).

Through the targeted selection of pertinent features, we aimed to discern the most influential variables contributing to the collective learning processes within group settings. Such meticulous feature selection methodologies are pivotal in uncovering the underlying determinants of group learning, offering a pathway for enhancing educational strategies and optimizing collaborative learning environments. In the present study, two feature selection methodologies were employed, specifically (1) Mutual Information (MI) and (2) Recursive Feature Elimination (RFE) with regard to logistic regression that facilitated a focused exploration into the influence of different variables on the dynamics of tandem learning.

The analysis of MI has shown that the most influential factor that affects tandem learning efficacy is outperforming the partner. Thus, students who were more successful in tandem learning also reported greater effectiveness of tandem learning (MI = .22). Also, the RFE ranking for this variable has confirmed its importance (RFE = 1). Among the other most important factors, qualitative interaction with the partner has been recognized (MI = .08; RFE = 1). This fact has been corroborated also by previous research that has shown that working in small groups leads to more effective learning compared with traditional instruction (Kalaian et al., 2018). Qualitative interaction refers to meaningful and task-focused communication among tandem members, emphasizing discussions related to the mathematical problem at hand rather than unrelated or trivial topics, thereby contributing to a more effective collaborative learning environment (Tissenbaum, 2020).

Notably, although qualitative interaction and the performance of the individual emerged as pivotal aspects, traditional personality variables such as motivation, anxiety, and traits from the MBTI test (introversion, judging, sensing, and feeling) did not significantly impact the dynamics of tandem learning.

Considering gender, our findings are supported by some pieces of the existing literature on the topic of small-group mathematics learning, which found no gender differences in the effectiveness of this learning model (McCaslin et al., 1994). Therefore, group composition based on students' gender does not affect the perceived effectiveness of tandem learning, suggesting that educators can create mixed boys-girls groups without penalizing one gender respect to the other (Webb, 1991). The fact that gender does not impact students' attitudes toward tandem learning might prevent them from feeling uncomfortable in a class setting and help them learn (Samuelsson & Samuelsson, 2016).

Additionally, the fact that motivation, anxiety, and students' personality traits do not influence to a large extent students' perception of the effectiveness of tandem learning suggests that the broader context and collaborative dynamics within these environments exert a more substantial influence than individual personality traits.

The observed result may find its roots in the unique way groups form within these settings as part of the teachers' experience in forming groups. The fact that students have the autonomy to choose their seating arrangement (often opting to sit with pre-existing friends) suggests a pre-established comfort level among group members (Hong & Lee, 2017). This setting potentially mitigates the need for extroversion to engage in communication or curbs anxiety, given the familiarity and ease of interaction among peers. Variables directly associated with tandem learning present a unique challenge regarding their predictive weight. Unlike general variables (e.g., gender, class, and psychological variables), these factors inherently emerge and manifest only after the implementation of tandem learning strategies. Their significance and impact cannot be reliably gauged beforehand. Consequently, the research underscores the necessity of not only assessing the variables that influence tandem learning beforehand but also continuously monitoring and evaluating the evolving dynamics during the collaborative process.

Our variables spanned a wide spectrum (categorical, continuous, and ordinal), making relationships complex and non-linear. Though we aimed for numerical values, these could not fully capture true significance. This complexity calls for more sophisticated modeling approaches to unravel the actual impact of these diverse variables on learning outcomes.

The insights gleaned from such focused analyses could contribute significantly to the development of tailored interventions and instructional strategies aimed at optimizing collaborative learning environments (Luan & Tsai, 2021; Yang et al., 2021). Moreover, this methodological precision may foster the creation of predictive models that better capture the complexity of group learning, enabling researchers and educators to anticipate and address challenges more effectively while enhancing the overall educational experience (Ciolacu et al., 2017; Kuleto et al., 2021; Luan & Tsai, 2021).

CONCLUSIONS

This study demonstrates that general variables and tandem-learning-related variables are the most important for predicting the success of this small-group learning method among Slovene high school students. These insights provide practical guidance for educators seeking to optimize the effectiveness of tandem learning by considering and leveraging these influential variables. The potential incorporation of gathered information needs to be investigated further.

The present study is not without limitations. As one of the main limitations, the present sample used a small sample, therefore findings cannot be generalized to the whole Slovenian high school population. We suggest additional research with bigger sample sizes to investigate in greater detail the factors that might influence the effectiveness of tandem learning. Additionally, the present research does not include a prediction of whether tandem learning is overall effective or not since it simply examines which variables impact student response. Some of the variables that are likely relevant for group learning like economic, social, and cultural status (ESCS), place of birth (geographical region), school type, and others were also not taken into account. The dataset was also slightly unbalanced, as only 6.7% of students said the method was not successful, potentially hindering model accuracy. We also did not include how group composition affects the tandem learning enviroment. Exploring a broader range of factors in future studies could offer a more comprehensive understanding of the complex factors influencing student perception of tandem learning. Further research encompassing broader datasets and employing more intricate modeling techniques could address these limitations, enhancing the robustness and applicability of findings in the domain of group learning dynamics.

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