# 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 89 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 and recursive feature elimination for all variables.

### Results

The most important variables according to mutual information for predicting student response were gender, class and qualitative interaction within group (Mi scores of 0.26, 0.09 and 0.08 respectively) and according to recursive feature analysis qualitative interaction, outperforming partner and gender (all with rank 1).

### 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).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 was 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 (Moreno-Guerrero et al., 2020; Puklek, 2001; Rau & Heyl, 1990) | 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 (Slavin et al., 2003; Van Der Laan Smith & Spindle, 2007), while gender (Gnesdilow et al., 2013; Rodger et al., 2007) could exert a somewhat influential role. Data on how professor and belonging class impact group learning is scarce, aside from general instructions for teachers how said method should be implemented like (McCaslin & Lowman, 1985).

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). Mathematical motivation is a factor negatively correlated to mathematical anxiety (Bregant & Doz, 2024). Collaborative learning activities have been conceived as a source of influence on individual motivation (Järvelä et al., 2010).

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.

#### Group forming

Razni viri, o kaksnih skupinah govorimo. Zakaj so mešani tipi dobri / slabi, enako spol.... Tomić 2003, https://doi.org/10.1016/J.IJER.2018.09.004 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.

A black arrow pointing to a square

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Figure 2: 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 minimum 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). Further objectives associated with feature selection encompass enhancing generalization performance relative to models utilizing the entire feature set, fostering robust generalization and promptness in processing unseen data, and ultimately attaining a clearer and more straightforward comprehension of the data generation process (Vergara & Estévez, 2014).

# Empirical work

## Research problem, goals, hypothesises and methodology

Investigating tandem learning involves understanding the diverse elements that impact this collaborative approach. The research seeks to uncover how various variables interact within tandem learning setups to enhance overall educational effectiveness. The research problem revolves around deciphering 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.

Based on litterature about different effects on tandem learning, we formed general hypothesis: Some variables impact tandem learning more than others and specific hypothesis: Variables regarding tandem learning itself have greater impact.

## Sample

The sample was comprised of 89 students from 11th (approx. 16 years old) and 12th (approx. 17 years old) grade of a Slovenian Gymnasium (i.e., high school). Fifty-six diverse questions were assessed and condensed into 14 variables, one of which (outcome of interest) was a three state variable capturing student preferences toward the method, rated on a Likert scale. Three predictor variables were categorical in nature, while others were numeric, but treated as continuous.

## 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 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 (qualitative interaction, quantitative interaction and whether student outperformed 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 – purely by teacher’s judgement. 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 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).

### Instruments used

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 MBTI. Data was gathered from (*Myers-Briggs/Jung Test: Open Extended Jungian Type Scales*, n.d.), 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 mathematical motivation was gathered from (Sundre et al., 2012) (as part of ATMI test), while mathematical anxiety questioonaire (AMAS test) was gathered from (*PsyToolkit*, n.d.). AMAS and ATMI 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”) as the shift towards employing continuous scales aims to mitigate the polarizing effect often associated with categorical classificat (Ramsay et al., 2000). That can also lead to better model accuracy (Carlson, 1985; Carlyn, 1977; DeVito, 1985). The survey utilized established elements with slight adaptations to accommodate diverse cultural and social contexts, while keeping the instrument constructs consistent.

### Data analysis

The gathered data was analysed using Python programming language, primarily using pandas (version 3.11.4) and scikit-learn (version 1.3.2) libraries. Raw anonymized dataset with statistics code is openly accessible on (Bregant, 2023).

In suma, we modified all data in the form of tidy data (Wickham, 2014). Label encoding was used to tackle categorical variables (Gender, Professor 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 substantiate the hypothesis on feature importance, we employed mutual information and recursive feature elimination methodologies, chosen for their capability to effectively handle a blend of continuous and categorical data in tandem, ensuring a robust validation process.

## Results

In pursuit of internal consistency, we adopted McDonald's Omega for continuous variables and Gutman's Lambda (bolj za likertove?) for categorical variables, ensuring a comprehensive assessment across different data types for a holistic analysis. Internal consisetency is fair for continuous variables, while for categorical variables the confidence interval is a bit wide.

|  |  |  |
| --- | --- | --- |
| Internal consistency measure | Value | 95% confidence interval |
| McDonald's Omega | 0.53 | [0.53, 0.54] |
| Gutman's Lambda | 0.45 | [0.32, 0.57] |

MCA iz prince knjižnice, ki handla oboje mi ne dela...

### Student sample

Dataset description with quantile information can be found in tables below.

|  | Successfulness | Grade | Interaction  quantitative | Interaction  qualitative | Outperforming  partner | Class | Professor | Gender |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| count | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 |
| mean | 2.43 | 3.39 | 2.18 | 2.09 | 2.07 | 2.62 | 1.93 | 0.69 |
| std | 0.62 | 0.97 | 0.65 | 0.68 | 0.56 | 2.11 | 1.17 | 0.47 |
| min | 1.0 | 2.0 | 1.0 | 1.0 | 1.0 | 0.0 | 0.0 | 0.0 |
| 25% | 2.0 | 3.0 | 2.0 | 2.0 | 2.0 | 1.0 | 1.0 | 0.0 |
| 50% | 2.0 | 3.0 | 2.0 | 2.0 | 2.0 | 3.0 | 2.0 | 1.0 |
| 75% | 3.0 | 4.0 | 3.0 | 3.0 | 2.0 | 4.0 | 3.0 | 1.0 |
| max | 3.0 | 5.0 | 3.0 | 3.0 | 3.0 | 6.0 | 3.0 | 1.0 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Anxiety | Motivation | Introversion | Sensing | Feeling | Judging |
| count | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 | 89.0 |
| mean | 25.8 | 20.38 | 20.58 | 22.71 | 23.33 | 22.8 |
| std | 6.8 | 6.27 | 5.57 | 4.54 | 4.68 | 5.68 |
| 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 |

Distribution of target and predictor variables can be found in figure below. We employed the Shapiro-Wilk test to assess the normality of certain variables, although this step was not essential as our selected methodologies, specifically MI and RFE 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 predictive modeling. All the variables tested look Gaussian. Related normality fittings and QQ-plots can be found in Appendix B, while p-values can be found in (Bregant, 2023).

A group of graphs with different colored bars

Description automatically generated with medium confidence

Exploring the correlation provides valuable insights into the relationships between variables, aiding in the identification of potential associations and dependencies crucial for understanding the interplay and potential influence among different factors within the dataset.A diagram of a person's personality

Description automatically generated with medium confidence

### Variable importance

A graph with red green and blue bars

Description automatically generated

A graph of a bar graph

Description automatically generated

|  |  |  |
| --- | --- | --- |
| Variable | Mutual information | RFE ranking (less is more important) |
| Gender | 0.236 | 1 |
| Class | 0.087 | 5 |
| Interaction\_qualitative | 0.083 | 1 |
| Professor | 0.038 | 3 |
| Outperforming\_partner | 0.018 | 1 |
| Anxiety | 0.005 | 8 |
| Grade | 0.000 | 4 |
| Interaction\_quantitative | 0.000 | 2 |
| Motivation | 0.000 | 11 |
| Introversion | 0.000 | 10 |
| Sensing | 0.000 | 6 |
| Feeling | 0.000 | 7 |
| Judging | 0.000 | 8 |

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 |
| 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 – outperform) | Tandem learning |

## Discussion

In this case study, we employmed feature selection methodologies, specifically Mutual Information (MI) and Recursive Feature Elimination (RFE) that facilitated a focused exploration into the influence of different variables on the dynamics of tandem learning – a specific case of group learning. Through the targeted selection of pertinent features, we aimed to discern the most influential variables contributing to the collective learning processes within group settings.

Through the judicious application of MI and RFE in feature selection, we identified a subset of key variables crucial in shaping group learning dynamics. This approach not only streamlined the feature set but also provided valuable insights into the relative importance of different variables, paving the way for a more focused understanding of the factors driving collaborative learning outcomes within group environments. 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.

Surprisingly, while gender, class, 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 cooperative learning. This insight challenges preconceptions, suggesting 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. 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. 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 like gender or class and psychological variables, these factors inherently emerge and manifest only after the implementation of cooperative learning strategies. Their significance and impact can't be reliably gauged beforehand. Consequently, it underscores the necessity of not only assessing the variables that influence cooperative 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 couldn't fully capture true significance. This complexity calls for more sophisticated modeling approaches to unravel the actual impact of these diverse variables on learning outcomes. Therefore applications of Chi-square, ANOVA and Kruskal-Wallis measures would not be optimally suited for this spectrum, respectively. They can however be found in Appendix C.

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. 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.

Some authors have however argued that students should not be forced to use learning approaches that do not suit their cognitive style.

## Conclusions and limitations

This study demonstrates that general variables and variables directly connected to tandem learning are most important for predicting success of said method 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.

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 economic, social and cultural status (ESCS), place of birth (geographical region)... were also not taken into account as ....(CITAT). The dataset was also slightly unbalanced as only 6.7% of students said the method was not succesfull, potentially hindering model accuracy. We also did not include how group composition affects 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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# Appendices

## Appendix A: Questionnaire

|  |  |  |
| --- | --- | --- |
| Target variable  (Likert scale 1 - 3) | 1 | Did you find the method (tandem learning) overall successive? Take into account both perspectives of improving math skills as well as school work diversification. |
| Mathematical motivation test  (Likert scale 1 - 5)  ((R) means reversily scored) | 2 | I plan to take as much mathematics as I can during my education. |
| 3 | I would like to avoid using mathematics in college (R) |
| 4 | The challenge of math appeals to me |
| 5 | I think studying advanced mathematics is useful |
| 6 | I am comfortable expressing my own ideas on how to look for solutions to a difficult problem in math |
| 7 | I really like mathematics |
| 8 | Mathematics is dull and boring (R) |
| Mathematical anxiety test  (How anxious you would feel during the event specified)  (Likert scale 1 - 5) | 9 | Having to use the tables in the back of a mathematics book |
| 10 | Thinking about an upcoming mathematics test one day before |
| 11 | Watching a teacher work an algebraic equation on the blackboard. |
| 12 | Taking an examination in a mathematics course |
| 13 | Being given a homework assignment of many difficult problems which is due the next class meeting |
| 14 | Listening to a lecture in mathematics class |
| 15 | Listening to another student explain a mathematics formula |
| 16 | Being given a “pop” quiz in a mathematics class |
| 17 | Starting a new chapter in a mathematics book |

|  |  |  |  |
| --- | --- | --- | --- |
| Personality MBTI test  (Likert scale 1 - 5)  (For each pair, you must choose where on the scale between them you think you are) | 18 | makes lists | relies on memory |
| 19 | sceptical | wants to believe |
| 20 | bored by time alone | needs time alone |
| 21 | accepts things as they are | unsatisfied with the ways things are |
| 22 | keeps a clean room | just puts stuff where ever |
| 23 | thinks "robotic" is an insult | strives to have a mechanical mind |
| 24 | energetic | mellow |
| 25 | prefer to take multiple choice test | prefer essay answers |
| 26 | chaotic | organized |
| 27 | easily hurt | thick-skinned |
| 28 | works best in groups | works best alone |
| 29 | focused on the present | focused on the future |
| 30 | plans far ahead | plans at the last minute |
| 31 | wants people's respect | wants their love |
| 32 | gets worn out by parties | gets fired up by parties |
| 33 | fits in | stands out |
| 34 | keeps options open | commits |
| 35 | wants to be good at fixing things | wants to be good at fixing people |
| 36 | talks more | listens more |
| 37 | when describing an event, will tell people what happened | when describing an event, will tell people what it meant |
| 38 | gets work done right away | procrastinates |
| 39 | follows the heart | follows the head |
| 40 | stays at home | goes out on the town |
| 41 | wants the big picture | wants the details |
| 42 | improvises | prepares |
| 43 | bases morality on justice | bases morality on compassion |
| 44 | finds it difficult to yell very loudly | yelling to others when they are far away comes naturally |
| 45 | theoretical | empirical |
| 46 | works hard | plays hard |
| 47 | uncomfortable with emotions | values emotions |
| 48 | likes to perform in front of other people | avoids public speaking |
| 49 | likes to know "who?", "what?", "when?" | likes to know "why?" |

|  |  |  |
| --- | --- | --- |
| General questions | 50 | Previous grade in mathematics |
| 51 | Class |
| 52 | Gender |
| 53 | Professor |
| Tandem work related  (Likert scale 1-3) | 54 | Evaluate how much interaction (quantitative) was at your station |
| 55 | Evaluate how productive was said interaction |
| 56 | Did you outperform your tandem partner? |

## Appendix B: Normality tests

A graph and diagram of a graph

Description automatically generated with medium confidenceA graph and diagram of a graph

Description automatically generated with medium confidenceA graph and diagram of a graph

Description automatically generated with medium confidenceA graph and diagram of a graph

Description automatically generated with medium confidenceA comparison of a graph

Description automatically generatedA graph and diagram of a graph

Description automatically generated with medium confidence

## Appendix C: Other statistics for measuring significance

Chi-square test p-value for Gender: 0.684

Chi-square test p-value for Class: 0.355

Chi-square test p-value for Professor: 0.394

ANOVA p-value for Motivation: 0.468

ANOVA p-value for Anxiety: 0.091

ANOVA p-value for Introversion: 0.596

ANOVA p-value for Sensing: 0.549

ANOVA p-value for Feeling: 0.550

ANOVA p-value for Judging: 0.246

Kruskal-Wallis p-value for Grade: 0.717

Kruskal-Wallis p-value for Interaction\_quantitative: 0.245

Kruskal-Wallis p-value for Interaction\_qualitative: 0.048

Kruskal-Wallis p-value for Outperforming\_partner: 0.553