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Uncovering Key Educational Predictors of GPA in Mathematics Education Undergraduates: A Decision Tree Classification Study

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Abstract: Student academic achievement in the form of Grade Point Average (GPA) is one of the measures to assess the quality of learning. Not only are individual cognitive factors a determinant of students' high GPAs, but other non-cognitive factors can affect GPA achievement. Therefore, this study aims to examine the factors that influence academic achievement, as measured by GPA. This study was a descriptive quantitative study involving 63 mathematics education student respondents, to identify the factors that influence the GPA achievement of students in the mathematics education study program. The data was analyzed descriptively and tested using a decision tree. Based on the decision tree algorithm, the results showed that learning methods were the dominant factor in classifying student GPA achievements, specifically whether the GPA of 3.50 or higher or less than 3.50. Students with a GPA of 3.50 or higher tend to benefit positively from discussion-based learning methods, while those with a GPA of less than 3.50 tend to engage more with traditional learning approaches. In addition to learning methods, factors such as the reason for choosing the study program, parents' educational background, and the duration of independent study time also contribute to strengthening or weakening students' GPA achievements. In the model evaluation results, the decision tree algorithm showed good predictive performance, demonstrating its effectiveness in classifying students based on their GPA achievement levels. Therefore, the results of this study can serve as a reference for educators and educational institutions to design more effective pedagogical strategies that not only strengthen cognitive skills but also foster the holistic development of students in mathematics education programs.

Keywords: classification, decision tree, grade point average, mathematics education.

▪ INTRODUCTION

The quality of learning can be observed in the academic achievements of students, including those at the higher education level. Sawiji et al. (2024) stated that one of the main objectives to fulfill the quality of learning outcomes is academic achievement. Through the academic achievements of students, universities can gauge the success of the learning process carried out. Nurmalitasari et al. (2023) state that through this, universities can identify, including by being part of the evaluation process, and early prevent students who are at risk of experiencing failure in the study process.

Sawiji et al. (2024) stated that academic performance is a relative thing to be determined with an appropriate measure because many factors and conditions must be considered to formulate academic performance. It was further explained that the definition of academic performance in the form of academic achievement requires a multidimensional approach (Alj & Bouayad, 2024; Meyer & Reynolds, 2022; Sawiji et al., 2024), which has an impact on the existence of intense competition in the higher education sector (Fajnzylber et al., 2019; Gordanier et al., 2019; Helal et al., 2018). One of the variables that can be used as a measure in assessing academic performance or student academic achievement is the grade point average (GPA) (Fajnzylber et al., 2019; Giunchiglia et al., 2018) which ranges from 1 to 4. Thus, one indicator that can be used

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to assess the academic performance of university students is the acquisition of a GPA, where the higher the GPA value obtained, the higher the grade received by the student.

The recognition of academic performance, as evidenced by a student's GPA, indicates that academic achievement is one of the key eligibility factors that can reflect a student's ability. Fajnzylber et al. (2019) stated that many universities explicitly instruct lecturers to improve their students' academic performance and achievement. In addition, the Indonesian government, through the Ministry of Higher Education, Science and Technology, explicitly seeks to improve student academic achievement, including GPA acquisition, through various programs initiated, not least for mathematics education study programs. Lecturers are instructed to implement learning that provides extensive opportunities for students to be active in the process of acquiring in-depth knowledge, namely through problem-based learning or case study learning. This is based on several research results that show the positive impact of implementing learning, one of which is problem-based learning (Beier et al., 2019; Chen & Yang, 2019; Darmuki et al., 2023; Usmeldi & Amini, 2022; Yang et al., 2020).

The acquisition of student academic achievement, including GPA, is not only influenced by the learning instructions provided by lecturers in the learning process. Sawiji et al. (2024) stated that the nature of academic performance, including the acquisition of GPA, is multifaceted so that various factors, both internal and external, can influence it. This is also corroborated by several other opinions that the acquisition of GPA, both directly and indirectly, is influenced by other factors, not only instructional or learning models provided (Brezavšček et al., 2020; Giunchiglia et al., 2018; Muenks et al., 2018; Samaha & Hawi, 2016; Thiele et al., 2016). This suggests that the acquisition of student academic achievement, as measured by GPA, is not only dependent on the learning methods employed but is also influenced by other factors, both direct and indirect. Thus, it is also essential to look at a holistic approach in measuring student academic performance.

Specifically, in the field of mathematics, Papanastasiou (2000) distinguishes between internal and external factors that can affect academic achievement. Internal factors are related to the test material, while external factors are related to the environment surrounding the individual. Furthermore, Enu et al. (2015) stated that successful academic achievement depends on student factors (initial behavior, motivation, and attitude), socio-economic factors (parental education and economic status), and school-based factors (availability of school facilities and infrastructure, type of school, and school characteristics). Brezavšček et al. (2020) stated that three variables can affect academic achievement in general, namely: (1) psychological factors that include several aspects including attitudes and anxiety, intelligence, self-concept, learning habits, aptitude, and motivation; (2) social factors that include socioeconomic status, school and home environment, parental education and involvement, parental employment and income, social relationships, type of school, and social maturity; and (3) biographical and instructional factors that include aspects of gender, locality, teaching methods, birth order, and home tutoring. These three factors are typically studied together in most studies, but they often focus on more specific aspects of each factor.

Research related to factors that affect academic achievement, namely GPA, has been conducted. Anisa & Permana (2022) stated that there are four out of eight factors that are thought to affect GPA acquisition, namely gender, major, admission type, and duration of using gadgets. In contrast to that study, this study proposes six additional, more diverse, and comprehensive factors that encompass social, instructional, and technology use aspects. With a broader range of factors, this study is expected to provide a more in-depth description of the variables that potentially affect students' GPAs. These factors refer to Brezavšček et al. (2020) as previously stated. The inclusion of six factors in this study refers not only to the findings of the study, but also to considerations of the real context faced by mathematics education students in Indonesia. Some of these factors include social variables, such as parents' education, instructional variables (such as choice of major, study time, and learning method), and technological factors, such as internet use. Parents' educational background plays a significant role in shaping the family environment and influencing students' academic performance. This is as stated by Hidayatullah & Csíkos (2024) that parents' educational background tends to be involved in their children's studies. In addition to parental educational background, the reason for choosing a study program becomes an intrinsic motivation for students, reflecting their personal interests. Intrinsic motivation and satisfaction with the study program are very important predictors in the course of a student's studies, especially in relation to academic success (van Rooij et al., 2018).

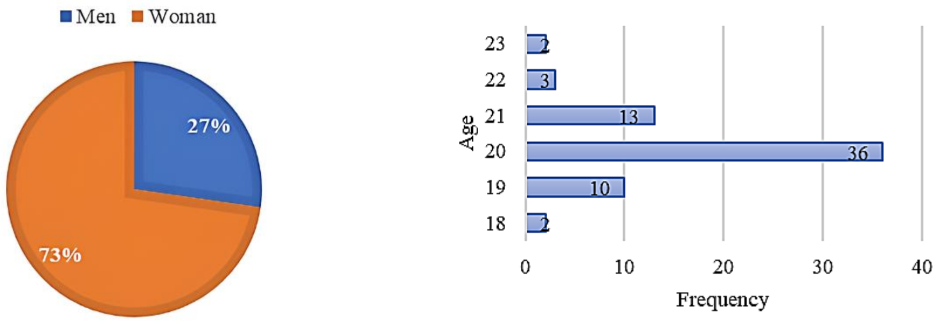
In addition to the two factors above, the duration of independent study, learning methods, and internet access are other factors that are potential predictors in classifying students based on their GPA achievements. The duration of independent study indicates how long students allocate their time outside of formal lectures to reinforce their understanding of lecture material. Suleiman, Okunade, Dada, & Ezeanya (2024) state that independent study time is one of the key factors that influence student academic performance. In addition, as an instructional factor, the learning methods used in the classroom can also activate student learning motivation, thereby impacting academic achievement (Wouters et al., 2016). Furthermore, technological factors such as internet access are becoming increasingly important in the context of education, including mathematics education. Access to the internet can be an alternative source of learning, so Ladrón de Guevara Rodríguez et al. (2022) state that the use of the internet for academic purposes has the potential to have a positive impact on academic achievement.

With a broader scope, this study aims to provide a comprehensive understanding of the factors that may influence GPA achievement. These factors are particularly relevant to mathematics education students, given their dual roles as learners and future educators, who are expected to foster a positive attitude towards mathematics. The addition of these factors reveals that academic achievement, as measured by GPA, is a complex and dynamic factor. Thus, students' academic achievement, especially GPA, is the result of a complex interaction of various factors, not only based on teaching models or methods. For this reason, a deep understanding of the dynamics of these factors is crucial so that they can be effectively utilized as part of the basis for evaluating the learning process. In addition, with understanding, universities can develop comprehensive policies to support students optimally, enabling them ultimately achieve their expected educational goals.

▪ METHOD

Participants

The research involved students from the Mathematics Education Study Program at a university in Central Java, Indonesia. The characteristics of the students in question are mathematics education study program students who have completed at least one semester of their program. A total of 66 students participated in this study, with the following distribution by gender and age.



(i) (ii)

Figure 1. Distribution of respondents by: (i) gender; (ii) age

Research Design and Procedures

This study employed a quantitative approach, utilizing a descriptive quantitative research method and data mining, to describe the factors influencing academic achievement based on the GPA of students in the Mathematics Education Study Program. Thus, specifically, this study aims to examine factors that can classify or predict a person with a GPA of 3.50 or higher versus one with a GPA less than 3.50.

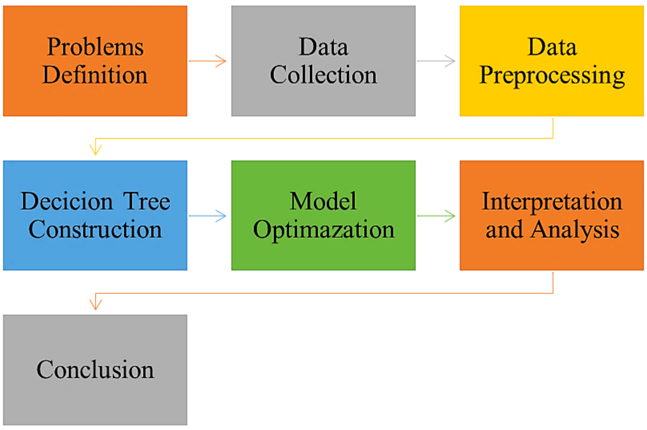


Figure 2. Research procedures

Decision trees are used to determine influencing factors. The research procedure begins with defining the research problem and identifying the target variables to be predicted, along with relevant features. After that, data is collected from reliable sources and processed through cleaning, transformation, and division into training and testing sets. During the pre-processing stage, categorical variables are first converted into numerical form through encoding (such as one-hot encoding) so that the algorithm can understand them. Numerical variables can be used directly because decision trees operate by determining division thresholds, although normalization or discretization options are available if needed. All these steps are performed with the help of the orange application through the Preprocess widget to ensure consistent and ready-to-use data. The decision tree model is constructed using the appropriate algorithm, followed by pruning to enhance performance and prevent overfitting. The model is evaluated using metrics such as accuracy, precision, recall, F1-score, and the Area Under the Curve (AUC) to assess its classification quality. Finally, the results are interpreted by analyzing the decision rules and feature importance, which provide meaningful insights.

Instruments

The factors referred to in this study are presented in Table 1 below, where the term factor in the table is expressed as an attribute.

Table 1. Attributes (factors) and their descriptions (Adopted from Brezavšček et al., 2020; Cortez & Silva, 2008)

Attributes	Descriptions	Remark
Grade point average (GPA) (Y)*	Numerical: 0 – 4	Target
Mother's education (X1)	Categorical (Multi): 0 No school; 1 Elementary school; 2 Junior high school; 3 Senior high school; 4 University	Fitur
Father's education (X2)	Categorical (Multi): 0 No school; 1 Elementary school; 2 Junior high school; 3 Senior high school; 4 University	Fitur
Reason for choosing the mathematics education study program (X3)	Categorical (Multi): 0 Near distance to domicile house; 1 Reputation of study program; 2 Courses offered; 3 Other	Fitur
Length of study time outside of lectures (Self-Study) (X4)**	Numeric: in hours	Fitur
Learning method (X5)***	Categorical (Multi): 0 Lecture method; 1 Discussion method; 2 Other	Fitur
Internet access (X6)	Categorical (Binary): 0 No; 1 Yes	Fitur

*GPA is classified into categories:1 for GPA < 3.50; 2 for GPA ≥ 3.50.
** Length of self-study represents the average number of hours of individual study per day.
*** Students' general perception of the learning methods used in the study program.

The data in this study were collected through a questionnaire administered to students in the mathematics education study program at one of the universities in Central Java, which was distributed via a Google Form during the 2023/2024 academic year. The dataset collected consisted of 66 data. However, after identification, it was found that three data did not match, so the data processed for further analysis consisted of 63 data using the Orange Data Mining tool. The data sample size in this study is relatively small, which may affect the results, especially in model evaluation. The model may perform well on training data but poorly on testing data.

Data Analysis

The data obtained were then analyzed descriptively and tested using the Decision Tree algorithm to identify the factors that influence the academic achievement of students in the mathematics education study program. Thus, based on this, it can be predicted that a student will be classified with a GPA of 3.50 or higher, or vice versa. Ul Hassan et al.

(2018) stated that a decision tree is a decision support method represented by a tree (such as a graph) or decision model to represent possible outcomes.

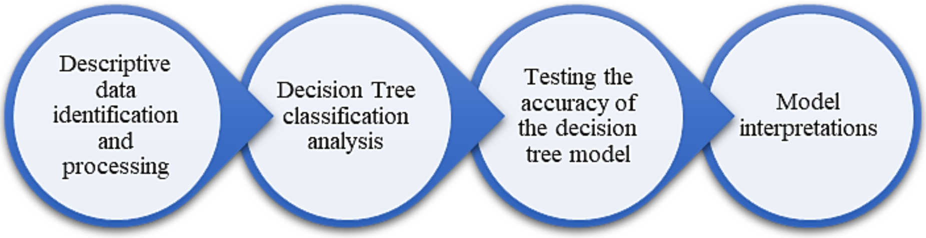


Figure 3. Data processing stages

Figure 3 illustrates the stages of data processing in decision tree classification. This process begins with the identification and processing of descriptive data, which includes collecting, cleaning, and preparing the dataset to ensure its suitability for analysis. The next stage is decision tree classification analysis, where the algorithm builds a model by mapping input features to target classes. This is followed by testing the accuracy of the decision tree model using evaluation metrics such as accuracy, precision, recall, and AUC to validate its predictive performance. The final stage is model interpretation, where extracted decision rules and feature importance are analyzed to provide meaningful insights and practical implications in the context of the research.

The decision tree algorithm consists of three components: the root node, branches, and leaf nodes (Smith & Bryant, 1975). It is explained that the root represents the decision to be made, the branch is the result of the root, and as a new branch, it represents the possibilities or consequences obtained from the decision-making process. Meanwhile, the leaf serves as an additional branch to explain the selected consequences. In a decision tree, the tree nodes represent attributes that have been tested, and each branch is a division of the test results, while the leaves are groups of certain classes (Han & Kamber, 2006). The root represents the attribute that has the most influence on a particular class. The basic concept of a decision tree is to convert data into a decision tree model, then convert it into rules, and simplify it (Setio et al., 2020).

▪ RESULT AND DISSCUSSION

Decision Tree Classification

The distribution of GPA achievements of the 63 respondents analyzed in this study is presented in Figure 2. Based on this data, 41% of respondents have a GPA less than 3.50, while 59% have a GPA of 3.50 or higher. Additionally, the analysis of demographic characteristics revealed that 73% of the respondents were female, while 27% were male. This information provides initial figures of the composition of the respondents as well as the distribution of their academic achievements.

The distribution of GPA, as presented in Figure 4, provides an initial indication of the trend in respondents' academic performance. The difference in the proportion of respondents with a GPA indicates the potential factors that affect the academic performance of respondents. This is in line with the opinion of Richardson et al. (2012) which states that differences in academic achievement, namely GPA gains, indicate the influence of internal and external factors. In addition, differences in the proportion of respondents based on gender can also provide additional insight, considering that several

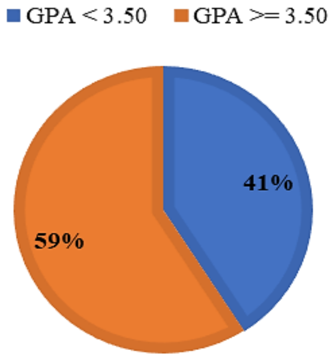


Figure 4. Distribution of GPA's respondents

studies reveal that female students tend to have better learning regulation abilities than men (Schunk & DiBenedetto, 2020). Thus, this data distribution analysis not only provides a descriptive picture but also opens up opportunities to understand the complex interactions between various factors that contribute to student academic achievement.

Furthermore, the analysis was conducted using a decision tree with the Orange application, following the procedure outlined in Figure 5. The results of the tree visualization are presented in Figure 6.

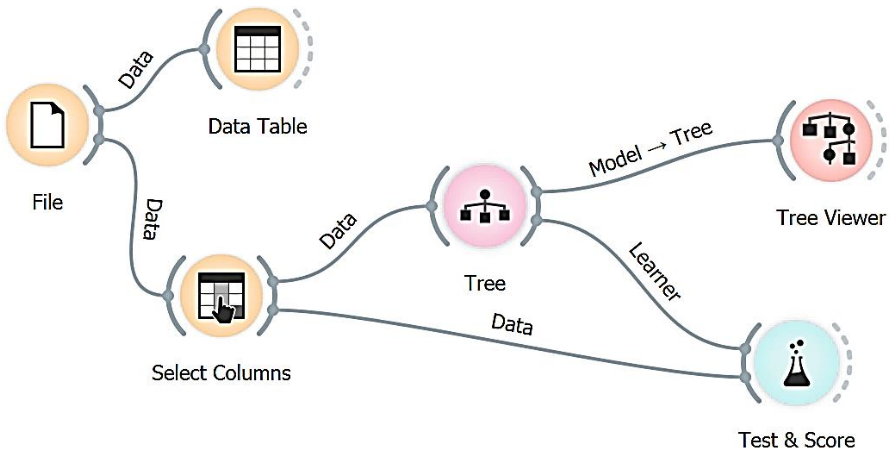


Figure 5. Data processing procedure in orange data mining

In Figure 6, the decision tree starts with factor X5, namely the learning method used in the mathematics education study program, as the root node in the tree formed. This shows that this factor is the main factor in dividing the data, which in this case makes the X5 factor the main factor that influences the acquisition of GPA with a probability value of 58.7%, the majority of data division leads to GPA group 2 (dark red color indicates the greatest probability), namely the GPA group more than or equal to 3.50, while the remaining 41.3% leads to GPA group 1, namely GPA less than 3.50. In general, referring to Figure 6, the branch and child nodes show the final dominance of the GPA classification. On the left branch, the distribution of GPA achievements is dominated by the GPA 2 class (red), which indicates a GPA of 3.50 or higher. In contrast, the right

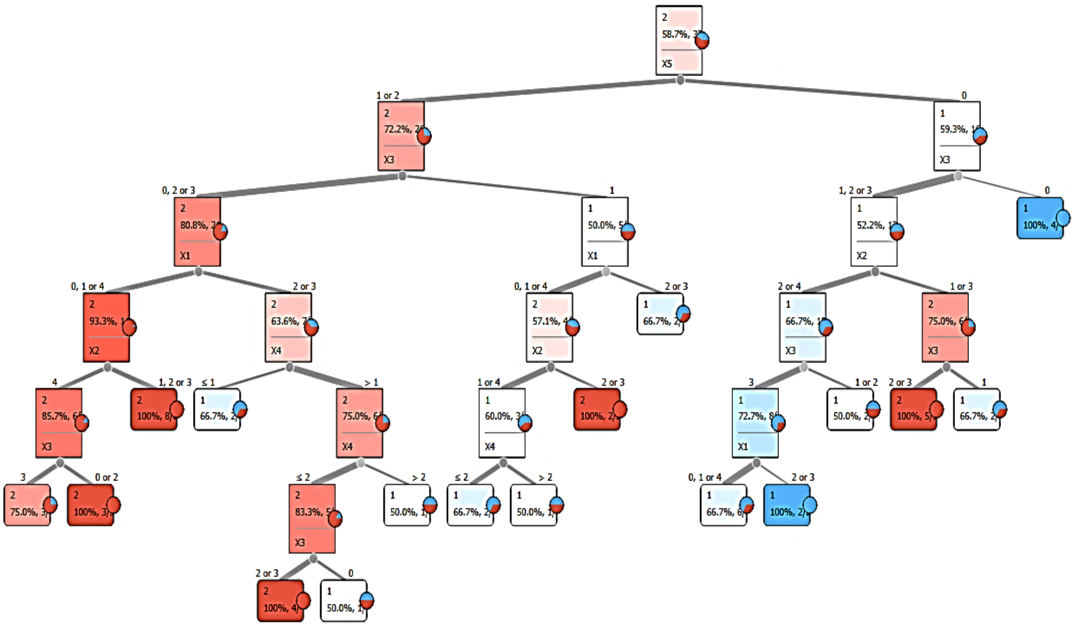


Figure 6. Overview of the decision tree model

ranch is dominated by the GPA 1 class (blue), which indicates a GPA of less than 3.50. However, this right branch will depend on several other additional factors.

Referring to the results above, differences in GPA achievement are influenced not only by individual characteristics but also by the learning process, particularly the learning methods employed in the classroom. This indicates that the learning methods employed in the classroom are one of the key factors in shaping students' academic achievement patterns, particularly their GPA. Learning methods that involve students, such as discussions, provide ample opportunities for students to construct and explore knowledge, thereby improving academic achievement. This is as stated by Lei, Cui, & Zhou (2018) that interactive learning methods, which allow students to be actively involved (student engagement), provide greater opportunities for academic achievement. In line with Lei et al., Luo, Chen, Yu, & Zhang (2023) stated that learning engagement can encourage better academic achievement among students. Thus, the learning method factor, as the primary dividing factor, is key in explaining GPA achievement.

Specifically, in the red GPA 2 group in Figure 7, i.e., a GPA of 3.50 or higher, if factor X5 meets criteria 1 or 2, i.e., it has a discussion method or another learning method. The tree branch moves to the left side towards factor X3, i.e., the reason for choosing the mathematics education study program, with a probability value of 72.2%. The results of this analysis show that students who use discussion-based learning methods tend to be associated with higher GPAs (≥ 3.50) or cum laude. These findings suggest that the learning methods employed in the classroom, combined with the presence of academic motivation in the form of strong reasons for choosing a study program, play a crucial role in achieving academic success. The discussion learning method provides ample opportunity for students to be active and cognitively involved, and provides a deep conceptual understanding of the material (Freeman et al., 2014; Ying, 2020). On the other hand, students who have intrinsic reasons for choosing a study program, such as interest or suitability with career goals, have a more positive impact on their motivation and

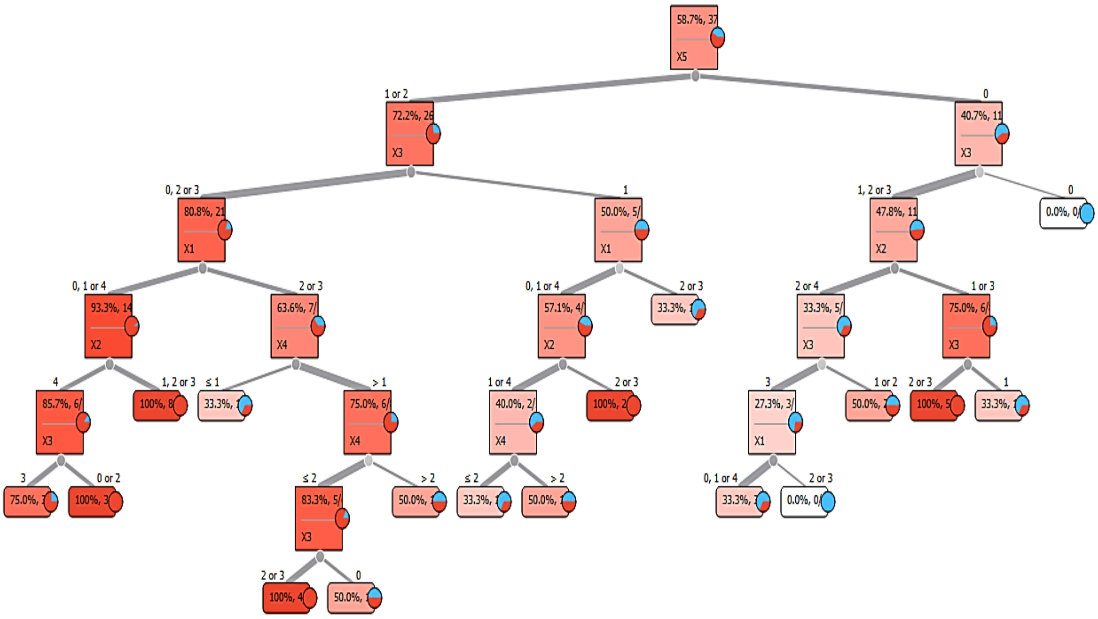


Figure 7. Model of decision tree for GPA of 3.50 or higher

involvement in the learning process (Méndez et al., 2025; Ryan & Deci, 2000; Shin, Jang, & Ihm, 2025).

In addition to the two factors above, achieving a GPA of 3.50 or higher in the X3 major is predicted to depend on factor X1, namely the mother's level of education. The initial probability value for factor X1 is 80.8%, which corresponds to a GPA of 3.50 or higher. Students with a higher parental educational background, specifically their mothers, tend to receive better academic support and resources, which has a positive impact on their mathematics achievement. This is in line with the research by Hidayatullah & Csíkos (2024), which shows that the relationship between highly educated parents and mathematics achievement is positive. On the other hand, other factors, namely X2 and X4, also appear to interact with X3. This indicates that not only maternal educational support, but also parents' education and independent study duration contribute to achieving a high GPA of more than 3.50 (Tamayo Martinez et al., 2022; Wang et al., 2020). Therefore, the factor of strong reasons for choosing a study program, supported by parental educational background and study duration, contributes to increasing students' chances of achieving a GPA of more than 3.50. Thus, the combination of motivational factors and family environment becomes an essential foundation in shaping students' academic success, specifically in achieving a high GPA.

In the GPA group with a GPA below 3.50, which is indicated in dark blue with the highest probability, Figure 8 shows a probability value of 41.3% for the distribution of respondents on factor X5 in the GPA group with a GPA below 3.50. Respondents will be classified in the GPA group below 3.50 when factor X5 is a learning method that does not facilitate student activity, particularly when characterized by lecturer dominance. In this case, X5 is the dominant factor in achieving a GPA of less than 3.50, where teaching methods dominated by lecturers or lacking interactivity, including those that are less suited to student characteristics, tend to reduce student engagement and academic performance. Kozanitis & Nenciovici (2023) state that learning using traditional methods,

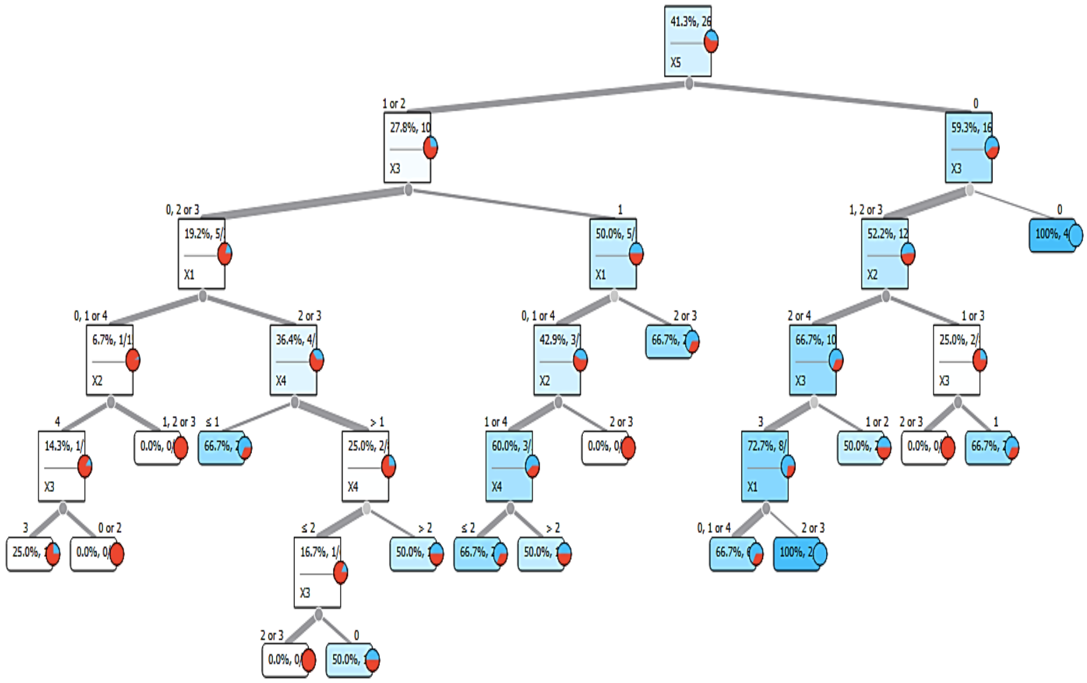


Figure 8. Model of decision tree for GPA less than 3.50

namely learning dominated by lecturers, shows lower average student achievement compared to learning that encourages student activity. Furthermore, a shift in the learning approach from a teacher-dominated method to a student-centered approach consistently shows an increase in student engagement and better learning outcomes compared to traditional methods (Baig & Yadegaridehkordi, 2023; Lee & Kim, 2018). Thus, when learning is conducted using teacher-dominated methods, such as expository methods, and there is a lack of student engagement, there is tendency for lower academic achievement.

In addition to factor X5, the educational background factors of both parents, namely X2 and X3, also moderate this relationship, whereby lower parental education levels are associated with limited learning support at home. This indicates that the role of parents' educational background is an important factor in students' academic achievement, including GPA (Hidayatullah & Csíkos, 2024; Munir et al., 2023; Wang et al., 2020). Furthermore, a higher level of parents' education is associated with the ability to provide academic guidance, learning motivation, and access to resources (Li & Qiu, 2018; Xiao et al., 2025)Thus, parental education as a social factor influences the success or failure of students in achieving academic success, including attaining a good GPA.

The factors of program selection (X3) and duration of independent study (X4) indicate factors that reinforce this pattern, namely that students who do not have strong intrinsic motivation in choosing a study program or who spend little or no time studying independently have a higher probability of having a GPA of less than 3.50. As stated by Ryan & Deci (2000) intrinsic motivation encourages engagement in the learning process and leads to higher academic performance. Students who choose a study program without strong intrinsic motivation tend to have lower learning outcomes. On the other hand, students with shorter independent study durations are at risk of obtaining a low GPA. Nonis & Hudson (2010) according to their research, independent study time shows a positive correlation with academic achievement, as well as with self-regulation and effective learning strategies. The more time spent on independent study, the higher the likelihood of achieving good academic performance. Thus, a combination of low intrinsic motivation and low study time contributes to an increased probability of students having a GPA of less than 3.50.

The findings of this study provide valuable insights into the multidimensional nature of academic achievement among mathematics education students. The identification of factors such as the teaching methods used in the classroom, the background of the study program selection, and parental educational background are potential determinants of GPA achievement, indicating that academic achievement cannot be fully explained by cognitive ability alone. This suggests that universities should not only focus on cognitive interventions but also consider students' intrinsic motivation and their parents' educational backgrounds, so that the programs designed can increase students' motivation to learn and provide socio-emotional support, thereby positively impacting students' academic achievement, including their GPA. Furthermore, the results of this study contribute to a broader understanding of student learning success by integrating psychological and social perspectives in the analysis of academic achievement. Although the predictive model developed in this study is still exploratory in nature, these findings can serve as a basis for further research in developing a stronger and more generally applicable model of academic achievement.

Model Evaluation

In model formation, overfitting can occur, which is when the model appears to perform very well on training data because it has actually "memorized" specific patterns or even noise in the data. If this happens, the model may fail to generalize to new data, resulting in a decline in its performance on test data. This condition affects the interpretation of results because the decision rules generated may appear very detailed but lack practical meaning, and the analysis of feature importance may become biased. Therefore, careful evaluation using training and test data, as well as more robust methods such as k-fold cross-validation and pruning, are essential to ensure that the conclusions drawn from the model are truly reliable and meaningful. Model evaluation in machine learning algorithms, including decision trees, is a crucial aspect in determining the model's quality, as it involves understanding the model's predictive performance. This process aims to measure the model's ability to classify data with optimal accuracy and precision.

Model evaluation was performed using a split dataset, with an 80:20 ratio for the training set and the testing set. Split validation is performed as a simple validation method that directly evaluates model performance. This technique divides the dataset into training data and test data, allowing researchers to assess the model's capabilities. Dividing the data into 80%-20% is considered a balance between the model's need to learn patterns and the need for evaluation on new data. Additionally, this ratio is a standard practice in machine learning that aims to achieve stable performance. The use of the split validation method with an 80%-20% ratio on a small dataset (N = 63) remains justified because it maintains a balance between sufficient training data to learn patterns and adequate test data to evaluate the model's generalization ability. Several literature sources also confirm that a simple division, such as 80%-20% is a common practice and remains valid for small datasets as long as the data is well randomized (James et al., 2021). The model evaluation results are presented in Table 2 below.

Table 2. Model evaluation

Method	AUC	CA	F1	Precision	Recall
Tree	0.886	0.794	0.794	0.844	0.794

The Area Under the Curve (AUC) value is 0.886, which is used to distinguish between groups. This value is in the considerable category (Çorbacıoğlu & Aksel, 2023), indicating that the model has excellent classification capabilities in distinguishing between categories of student GPA achievement, specifically those with a GPA greater than or equal to 3.50 and those with a GPA less than 3.50. In addition, with a classification accuracy (CA) value of 0.794, a precision of 0.844, and a recall of 0.794, the model shows promising predictive potential and demonstrates relatively balanced classification performance within the limited sample size, identifying students with specific GPA achievements. Thus, based on these evaluation values, the predictor factors used show a strong and consistent relationship with GPA achievement. Furthermore, the results obtained indicate that analysis using decision trees can serve as a basis for interpreting the dominant factors that influence student academic success, particularly in achieving a high GPA.

▪ CONCLUSION

Academic achievement, including the acquisition of GPA, for students in mathematics education study programs, does not depend only on student cognitive factors. Analysis of the decision tree algorithm reveals that several factors can be used to classify student GPA achievements, specifically those with a GPA of 3.50 or higher and those with a GPA less than 3.50. Learning methods are the most significant factor, followed by reasons for choosing a study program, parents' educational background, and the duration of independent study undertaken by students. Meanwhile, technological factors such as internet access are minor factors that serve as supporting factors. Among students with a GPA of 3.50 or higher, active learning methods, such as discussion-based approaches, have a positive impact on achieving a higher GPA. Additionally, factors such as reasons for choosing a study program and mothers' educational backgrounds also support student learning. Conversely, among students with a GPA of less than 3.50, traditional learning methods, dominated by lecturers, correlate with GPA achievement. Additionally, low intrinsic motivation in choosing a study program and a parental educational background also contribute to achieving this GPA. Thus, these factors provide empirical evidence that student GPA achievement can be improved by enhancing the quality of learning methods and strengthening students' intrinsic motivation and independent learning habits.

This study has limitations in terms of sample size, so it is recommended that future studies involve a larger sample size. Future studies may consider the diversity of institutions in the sample and the diversity in testing the model found. In addition, based on these findings, further research is recommended to examine the effectiveness of active learning models in enhancing student academic achievement, thereby improving GPA. In addition, the involvement of affective and other non-cognitive variables can be considered to gain a comprehensive understanding of the factors that impact student academic achievement.

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