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# Mapping Students' Perceptions of Mathematics Learning: A Principal Component Analysis Study

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**ABSTRACT**

This study investigated the multidimensional landscape of students' perceptions of mathematics learning using principal component analysis (PCA). Data were collected from 102 high school students (grades 9-12, mean age 16.2 years) in Indonesia. The survey, adapted from validated scales including the Fennema-Sherman Mathematics Attitudes Scales and the Attitudes Towards Mathematics Inventory, assessed various aspects of mathematics learning perceptions. Analysis revealed fifteen initial components that were subsequently consolidated into two major factors. The first factor encompassed variables related to external and environmental aspects: learning interest, parental support, motivation, difficulties, resources, school facilities, approaches, classrooms, materials, and methods. The second factor comprised internal and cognitive elements: conceptual understanding, self-confidence, learning models, anxiety, and techniques. The PCA results highlight the complex interplay between cognitive, affective, and contextual factors in mathematics learning. The findings suggest that interventions should adopt a holistic approach, addressing both environmental and cognitive dimensions. This research contributes to educational practice by identifying key areas for targeted intervention while demonstrating the effectiveness of PCA in understanding complex educational phenomena. Future studies could explore these factors' generalizability across different educational contexts and their longitudinal evolution.



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## 1. INTRODUCTION

In today's rapidly evolving educational landscape, understanding the role of core academic subjects has become increasingly crucial for student development and future success. Educational researchers and practitioners consistently emphasize the need for strong foundational skills that can prepare students for both academic challenges and real-world applications. Within this context, mathematics stands out as one of the most significant areas of study. Mathematics is a foundational subject that plays a pivotal role in developing critical thinking, problem-solving, and analytical skills essential for success in various academic and professional domains (B. Kaur, 2008; Weng, 2017). However, despite its importance, many students struggle with mathematics learning, often attributable to negative perceptions, lack of confidence, and anxiety towards the subject (Ashcraft & Ridley, 2005; Beilock & Maloney, 2015). These perceptions can significantly influence students' motivation, engagement, and ultimately, their academic achievement in mathematics (Asli & Iuliana, 2022; Gunderson et al., 2011). Numerous studies have highlighted the importance of understanding and addressing students' perceptions of mathematics learning, as these perceptions shape their attitudes, beliefs, and behaviors towards the subject (Di Martino & Zan, 2009; Fennema & Sherman, 1976; Zan & Di Martino, 2007). Positive perceptions, such as viewing mathematics as useful and relevant, having high self-efficacy, and experiencing intrinsic motivation, can foster a growth mindset and lead to improved performance and persistence in mathematics (Dweck, 2006). Conversely, negative perceptions, such as perceiving mathematics as overly difficult, experiencing high levels of anxiety, and lacking confidence, can contribute to avoidance, disengagement, and underachievement in the subject.

Students' perceptions of mathematics learning are multidimensional, encompassing various aspects such as perceived relevance, self-efficacy, teaching quality, intrinsic motivation, and perceived difficulty (T. Kaur & Prendergast, 2021; Mohamed & Waheed, 2011). However, these dimensions are often interrelated and may influence one another in complex ways. For example, students' self-efficacy beliefs can shape their intrinsic motivation and perceived difficulty, while the quality of teaching and classroom environment can impact their perceptions of relevance and enjoyment (Skaalvik et al., 2015). Understanding the underlying structure and interrelationships among these dimensions is crucial for developing targeted interventions and instructional approaches that address students' specific needs and concerns.

Principal component analysis (PCA) is a powerful multivariate statistical technique that can uncover the underlying dimensions or components that best represent the variability in a dataset (Jollife & Cadima, 2016). By applying PCA to survey data, researchers can identify the key factors that shape students' perceptions of mathematics learning and explore how these factors are related to one another. This approach has been successfully employed in various educational contexts to map students' perceptions and attitudes towards subjects such as science, technology, and engineering (Fitzpatrick & May, 2022). This study aims to map the multidimensional landscape of students' perceptions of mathematics learning by employing PCA on a comprehensive survey instrument. The survey instrument is designed to capture various aspects of students' perceptions, including perceived relevance, self-efficacy, teaching quality, intrinsic motivation, perceived difficulty, and anxiety towards mathematics. By identifying the underlying factors and their interrelationships, the findings will provide valuable insights into the key drivers influencing students' perceptions and their relative importance. These insights can contribute to a deeper understanding of this critical aspect of mathematics education and inform the development of targeted interventions, instructional strategies, and curriculum design aimed at fostering positive perceptions and enhancing students' engagement and achievement in mathematics learning.

Academic success hinges on a multitude of interrelated factors that shape a student's learning experience. Among these pivotal elements are learning interest, which refers to the inherent motivation and curiosity that drives the pursuit of knowledge (Kosovich et al., 2019) conceptual understanding, encompassing the comprehension and application of foundational principles (Rittle-Johnson & Schneider, 2015); and self-confidence, the belief in one's abilities to tackle academic challenges effectively (Stankov et al., 2014). Additionally, the learning model employed, whether traditional or innovative, can significantly impact the acquisition and retention of knowledge (Bergmann & Sams A, 2011). Parental support emerges as a critical component, providing emotional encouragement and practical assistance throughout the educational journey (Wang & Sheikh-Khalil, 2013). Closely tied to this is learning motivation, the driving force that propels students to engage with their studies and overcome obstacles (Lazowski & Hulleman, 2016). Conversely, learning difficulties and academic anxiety can hinder progress, presenting hurdles that must be addressed (Carey et al. 2017; Putwain et al. 2017). Furthermore, the availability and quality of learning resources, including textbooks, online materials, and multimedia aids, play a crucial role in facilitating effective learning (Xie et al., 2018).

The educational environment itself is a significant factor, with school facilities, such as well-equipped classrooms, libraries, and laboratories, contributing to a conducive learning atmosphere (Earthman, 2004). The pedagogical approaches adopted by educators, encompassing teaching methods, techniques, and classroom management strategies, can profoundly influence student engagement and comprehension (Forsey et al., 2013; Korpershoek et al., 2014). Moreover, the subject matter itself, including its depth, relevance, and presentation, can shape the overall learning experience (Quintana et al., 2004). Collectively, these variables – learning interest, conceptual understanding, self-confidence, learning models, parental support, motivation, difficulties, anxiety, resources, facilities, teaching approaches, techniques, classroom dynamics, and subject content – form an intricate tapestry that underpins academic achievement. By carefully considering and addressing each of these elements, educators and policymakers can create an environment conducive to fostering intellectual growth and empowering students to reach their full potential (Burusic et al., 2016; Wheeldon, 2010).

In summary, this study aims to elucidate the intricate interplay of factors influencing students' perceptions of mathematics learning. By employing principal component analysis, we endeavor to unravel the underlying dimensions that encapsulate variables such as learning interest, conceptual understanding, self-confidence, learning models, parental support, motivation, learning difficulties, academic anxiety, access to resources, school facilities, pedagogical approaches, teaching techniques, classroom dynamics, and subject content. Mapping these multifaceted elements will provide invaluable insights into the complex tapestry that shapes students' experiences with mathematics education. Ultimately, this research seeks to inform educational practices and policies, fostering an environment that nurtures intellectual growth, mitigates barriers, and empowers students to reach their full potential in mathematical pursuits. Understanding students' perceptions of mathematics learning is critically important for several compelling reasons. First, these perceptions directly influence students' engagement, motivation, and academic performance in mathematics, making it essential for educators and policymakers to have a clear understanding of how students view and experience mathematical learning. By employing Principal Component Analysis (PCA), this research offers a novel methodological approach to systematically map and analyze these perceptions, providing a more nuanced and data-driven understanding than previous qualitative studies. The findings from this research can significantly contribute to the development of more effective teaching strategies, curriculum design, and educational interventions that better align with students' cognitive and emotional needs in mathematics education. Moreover, by identifying key components that shape students' mathematical learning experiences, this study bridges an important gap in educational research and provides actionable insights for improving mathematics education outcomes across different learning contexts and student populations.

## 2. METHOD

The study employed a quantitative research design to investigate the underlying factors shaping students' perceptions of mathematics learning. The participants consisted of a sample of 102 high school students from schools in indonesia. The students were drawn from grades 9-12, with an average age of 16.2 years. The sample included representation from diverse ethnic and socioeconomic backgrounds to enhance the generalizability of the findings (Creswell & Creswell, 2021) A comprehensive survey instrument was developed to assess various aspects of students' perceptions of mathematics learning, including perceived relevance, self-efficacy beliefs, intrinsic motivation, perceptions of teaching quality, perceived difficulty, and mathematics anxiety. The survey comprised 15 items measured on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree." The items were adapted from previously validated scales, such as the Fennema-Sherman Mathematics Attitudes Scales (Fennema & Sherman, 1976) and the Attitudes Towards Mathematics Inventory (Tapia & Marsh, 2004). Rigorous validation procedures, including expert review, cognitive interviews, and pilot testing, were undertaken to ensure the survey's reliability and validity.

The survey was administered to the participating students during regular class hours, with the assistance of trained research assistants. Informed consent was obtained from both students and their parents or guardians, and participation was voluntary, adhering to ethical research practices (Creswell & Poth, 2018). Appropriate measures were taken to ensure the confidentiality of the participants' responses. The collected survey data underwent thorough screening and cleaning processes to handle missing values, outliers, and normality assumptions, following established guidelines for data preparation (Tabachnick & Fidell, 2013). The primary data analysis technique employed in this study was principal component analysis (PCA), a powerful multivariate statistical method that allows for the identification of underlying dimensions or components that best explain the variability in the data. The PCA was conducted following a systematic approach, including the computation of a correlation matrix, factor extraction using various criteria (e.g., eigenvalues, scree plot, parallel analysis) as recommended by Hayton, Allen, and Scarpello (2004), oblique rotation for enhanced interpretability, and factor interpretation based on the rotated factor loadings. Factor scores were computed for each participant, representing their scores on the extracted components.

Reliability and validity analyses were performed to assess the internal consistency, convergent validity, and discriminant validity of the extracted components, following established guidelines. Supplementary analyses, such as correlations and regression analyses, were conducted to explore the relationships between the identified components and relevant demographic variables or academic performance measures. The findings from the PCA and subsequent analyses were interpreted within the context of existing literature and theories related to students' perceptions of mathematics learning. Implications for educational practice, curriculum development, and future research directions were discussed based on the study's results, aligning with the recommendations of Creswell and Creswell (2018) for reporting quantitative research

## 3. RESULTS AND DISCUSSION

### 3.1. Result

From the results of data analysis of students' perceptions of mathematics learning which consists of 15 variables, namely interest in learning, understanding of concepts, self-confidence, learning models, parental support, learning motivation, learning difficulties, learning anxiety, learning resources, school facilities, learning approaches, learning techniques , classroom, learning materials, and learning methods obtained information regarding the mean, standard deviation and the number of N for each variable which is written in table 1 below.

Table 1. Mean, Standard Deviation, and N

| Variable | Mean | Std. Deviation | Analysis N |
|---|---|---|---|
| X1 | 3.83 | 1.044 | 102 |
| X2 | 3.77 | 0.922 | 102 |
| X3 | 3.8 | 0.944 | 102 |
| X4 | 3.75 | 0.969 | 102 |
| X5 | 3.78 | 0.886 | 102 |
| X6 | 3.75 | 0.906 | 102 |
| X7 | 3.63 | 1.004 | 102 |
| X8 | 3.87 | 0.897 | 102 |
| X9 | 2.34 | 0.96 | 102 |
| X10 | 3.75 | 0.982 | 102 |
| X11 | 3.76 | 0.946 | 102 |
| X12 | 3.78 | 0.919 | 102 |
| X13 | 3.77 | 0.964 | 102 |
| X14 | 3.81 | 0.864 | 102 |
| X15 | 3.93 | 0.893 | 102 |

Before carrying out factor analysis, KMO and Bartlett's Test analysis was first carried out, the results of which are shown in table 2 below.

Table 2. KMO and Bartlett's Test

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | 0.908 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 662.736 |
| | df | 105 |
| | Sig. | <.001 |

The results of data analysis show that the value of the Kaiser-Meyer-Olkin Measure of Sampling Adequacy is > 0.908, where this value is greater than 0.5. The results of data analysis also show that the Sig. of Bartlett's Test of Sphericity < 0.001 where this value is smaller than 0.05. From the results of the analysis, it was concluded that the variables were interest in learning, understanding of concepts, self-confidence, learning models, parental support, learning motivation, learning difficulties, learning anxiety, learning resources, school facilities, learning approaches, learning techniques, classrooms, subject matter, and the learning method is feasible and can be processed further using factor analysis techniques.

The results of the next analysis, namely anti-image matrices analysis, are useful for knowing and determining which variables are suitable for use in factor analysis. In the anti-image correlation section, it is known that the Measure of Sampling Adequacy (MSA) value for each variable studied is as follows. The learning interest variable has an MSA of 0.936. The concept understanding variable has an MSA of 0.886. The self-confidence variable has an MSA of 0.874. The learning model variable has an MSA of 0.882. The parental support variable has an MSA of 0.918. The learning motivation variable has an MSA of 0.899. The learning difficulties variable has an MSA of 0.897. The learning anxiety variable has an MSA of 0.904. The learning resources variable has an MSA of 0.942. The school facilities variable has an MSA of 0.900. The learning approach variable has an MSA of 0.951. The learning technique variable has an MSA of 0.930. The classroom variable has an MSA of 0.944. The subject matter variable has an MSA of 0.862. The learning method variable has an MSA of 0.896. The MSA value for all variables is > 0.50 so that the factor analysis requirements are met.

The next output is the communalities table which shows whether the variable values studied are able to explain the factors or not. A variable is considered capable of explaining a factor if the extraction value is > 0.50. Output communalities are shown in table 3 below.

Table 3. Communalities

| Component | Initial | Extraction |
|---|---|---|
| X1 | 1 | 0.582 |
| X2 | 1 | 0.519 |
| X3 | 1 | 0.621 |
| X4 | 1 | 0.619 |
| X5 | 1 | 0.417 |
| X6 | 1 | 0.659 |
| X7 | 1 | 0.604 |
| X8 | 1 | 0.503 |
| X9 | 1 | 0.441 |
| X10 | 1 | 0.555 |
| X11 | 1 | 0.446 |
| X12 | 1 | 0.56 |
| X13 | 1 | 0.476 |
| X14 | 1 | 0.477 |
| X15 | 1 | 0.474 |

Based on the output above, it is known that the extraction values for the variables interest in learning, understanding of concepts, self-confidence, learning models, parental support, learning motivation, learning difficulties, learning anxiety, learning resources, school facilities, learning approaches, learning techniques, classrooms, materials lessons, and learning methods are > 0.50. Thus it can be concluded that all variables can be used to explain factors. There are 15 variables so there are 15 components analyzed. There are three types of analysis results to explain a variance. The results of the first analysis are initial eigenvalues, extraction sums of squared loadings, rotation sums of squared loadings. In the initial eigenvalues analysis, it shows the factors that are formed. This analysis consists of total, percent of variance, and cumulative percent. The results of the initial eigenvalues analysis are shown in table 4 below.

Table 4. Initial Eigenvalues

| Component | Initial Eigenvalues | | |
|---|---|---|---|
| | Total | % of Variance | Cumulative % |
| 1 | 6.873 | 45.817 | 45.817 |
| 2 | 1.08 | 7.203 | 53.02 |
| 3 | 0.913 | 6.084 | 59.104 |
| 4 | 0.824 | 5.496 | 64.6 |
| 5 | 0.769 | 5.124 | 69.724 |
| 6 | 0.668 | 4.455 | 74.179 |
| 7 | 0.619 | 4.125 | 78.304 |
| 8 | 0.578 | 3.855 | 82.159 |
| 9 | 0.525 | 3.499 | 85.658 |
| 10 | 0.475 | 3.169 | 88.827 |
| 11 | 0.43 | 2.87 | 91.697 |
| 12 | 0.39 | 2.603 | 94.3 |
| 13 | 0.36 | 2.399 | 96.699 |
| 14 | 0.264 | 1.76 | 98.459 |
| 15 | 0.231 | 1.541 | 100 |

If the total of each component is added up (6.873 + 1.08 + ... + 0.264 + 0.231) it will show the number of variables, namely 15. Based on the results of the analysis, there are two factors formed from the 15 variables analyzed. This is indicated by the eigenvalues which are more than 1. The eigenvalues of the first component are 6.873, which means they are more than 1 and become first factor. The first component is able to explain 45.817% of the variation. The eigenvalues of the second component obtained a value of 1.08, which means it is more than 1 and is second factor. The second component is able to explain 7.203% of the variation. The eigenvalues of the third, fourth and fifth components are not factors because the eigenvalues are less than 1. So, there are two factors formed from 15 variables. If factors 1 and 2 are added together, they can explain 53.02% of the variation.

The second analysis is the extraction sums of squared loadings analysis which consists of total, percent of variance, cumulative percent. In the extraction sums of squared loadings analysis, it shows the number of factors formed. The results of the extraction sums of squared loadings analysis are shown in table 5 below.

Table 5. Extraction Sums of Squared Loadings

| Component | Extraction Sums of Squared Loadings | | |
|---|---|---|---|
| | Total | % of Variance | Cumulative % |
| 1 | 6.873 | 45.817 | 45.817 |
| 2 | 1.08 | 7.203 | 53.02 |

Based on the results of the analysis, there are two factors formed from the 15 variables analyzed. This is shown by the extraction sums of squared loadings value that is formed. The value of the extraction sums of squared loadings for the first component is 6.873, which means it is more than 1 and is first factor. The first component is able to explain 45.817% of the variation. The extraction sums of squared loadings value for the second component obtained a value of 1.08, which means it is more than 1 and is second factor. The second component is able to explain 7.203% of the variation. So, there are two factors formed from 15 variables. If factors 1 and 2 are added together, they can explain 53.02% of the variation.

The third analysis is the analysis of rotation sums of squared loadings which consists of total, percent of variance, cumulative percent. In rotation analysis, the sums of squared loadings show the number of variations or factors that are formed after rotation. The results of the rotation sums of squared loadings analysis are shown in table 6 below.

Table 6. Rotation Sums of Squared Loadings

| Component | Rotation Sums of Squared Loadings | | |
|---|---|---|---|
| | Total | % of Variance | Cumulative % |
| 1 | 4.82 | 32.13 | 32.13 |
| 2 | 3.133 | 20.89 | 53.02 |

Based on the results of the analysis, there are two factors formed from the 15 variables analyzed. This is indicated by the value of rotation sums of squared loadings that is formed. The value of the rotation sums of squared loadings of the first component is 4.82, which means it is more than 1 and is first factor. The first component is able to explain 32.13% of the variation. The rotation sums of squared loadings value of the second component obtained a value of 3.133, which means it is more than 1 and is second factor. The second component is able to explain 20.89% of the variation. So, there are two factors formed from 15 variables. If factors 1 and 2 are added together, they can explain 53.02% of the variation. Scree plots for eigenvalues and component numbers are shown in figure 1.

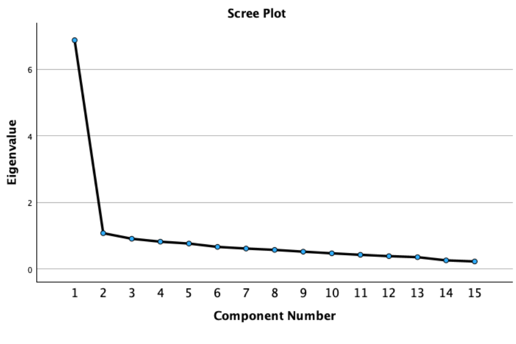


Figure 1. Scree Plot Eigenvalue and Component Number

The scree plot image can also show the number of factors formed. The method is to look at the component value points that have eigenvalues more than 1. There are 2 component points that have eigenvalues more than 1, so it can be interpreted that there are 2 factors that can be formed. The next output is a component matrix. This output shows the correlation value or relationship between each variable and the factors that will be formed. The component matrix output is shown in table 7 below.

Table 7. Component Matrix

| Component | 1 | 2 |
|---|---|---|
| X1 | 0.733 | -0.212 |
| X2 | 0.698 | 0.178 |
| X3 | 0.605 | 0.505 |
| X4 | 0.562 | 0.551 |

| Component | 1 | 2 |
|---|---|---|
| X5 | 0.644 | 0.052 |
| X6 | 0.729 | -0.358 |
| X7 | 0.754 | -0.189 |
| X8 | 0.638 | 0.309 |
| X9 | -0.615 | 0.249 |
| X10 | 0.716 | -0.204 |
| X11 | 0.658 | -0.119 |
| X12 | 0.736 | 0.136 |
| X13 | 0.685 | 0.082 |
| X14 | 0.672 | -0.16 |
| X15 | 0.678 | -0.121 |

Based on the output results, the following information is obtained. The correlation value of the learning interest variable with first factor is 0.733 and second factor is 0.212. The correlation value of the concept understanding variable with first factor is 0.698 and second factor is 0.178. The correlation value of the self-confidence variable with first factor is 0.605 and second factor is 0.505. The correlation value of the learning model variable with first factor is 0.562 and second factor is 0.551. The correlation value of the parental support variable with first factor is 0.644 and second factor is 0.052. The correlation value of the learning motivation variable with first factor is 0.729 and second factor is 0.358. The correlation value of the learning difficulties variable with first factor is 0.754 and second factor is 0.189.

The correlation value of the learning anxiety variable with first factor is 0.638 and second factor is 0.309. The correlation value of the learning resource variable with first factor is 0.615 and second factor is 0.249. The correlation value of the school facilities variable with first factor is 0.716 and second factor is 0.204. The correlation value of the learning approach variable with first factor is 0.658 and second factor is 0.119. The correlation value of the learning technique variable with first factor is 0.736 and second factor is 0.136. The correlation value of the classroom variable with first factor is 0.685 and second factor is 0.082. The correlation value of the subject matter variable with first factor is 0.672 and second factor is 0.16. The correlation value of the learning method variable with first factor is 0.678 and second factor is 0.121.

In determining which factor group a variable falls into, it can be determined by looking at the largest correlation value between the variable and the factors (components) formed. The results of the rotation model factor analysis are as follows. The output rotated component matrix is shown in table 8 below.

Table 8. Rotated Component Matrix

| Component | 1 | 2 |
|---|---|---|
| X1 | 0.715 | 0.266 |
| X2 | 0.455 | 0.559 |
| X3 | 0.186 | 0.766 |
| X4 | 0.124 | 0.777 |
| X5 | 0.487 | 0.425 |
| X6 | 0.798 | 0.146 |
| X7 | 0.718 | 0.297 |
| X8 | 0.329 | 0.628 |
| X9 | -0.643 | -0.166 |
| X10 | 0.697 | 0.262 |
| X11 | 0.599 | 0.296 |
| X12 | 0.51 | 0.548 |
| X13 | 0.502 | 0.474 |
| X14 | 0.635 | 0.271 |
| X15 | 0.617 | 0.306 |

Based on the output results above, the following information is obtained. The correlation value of the learning interest variable with first factor is 0.715 and second factor is 0.266. The correlation value of first factor > the correlation value of second factor, then the learning interest variable is included in first factor group. The correlation value of the concept understanding variable with first factor is 0.455 and second factor is 0.559. The correlation value of first factor < the correlation value of second factor, then the concept understanding variable is included in second factor group. The correlation value of the self-confidence variable with first factor is 0.186 and second factor is 0.766. The correlation value of first factor < the correlation value of second factor, then the concept understanding variable is included in second factor group.

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The correlation value of the learning model variable with first factor is 0.124 and second factor is 0.777. The correlation value of first factor < the correlation value of second factor, then the learning model variable is included in second factor group. The correlation value of the parental support variable with first factor is 0.487 and second factor is 0.425. The correlation value of first factor > the correlation value of second factor means that the parental support variable is included in first factor group. The correlation value of the learning motivation variable with first factor is 0.798 and second factor is 0.146. The correlation value of first factor > the correlation value of second factor, then the learning motivation variable is included in first factor group.

The correlation value of the learning difficulties variable with first factor is 0.718 and second factor is 0.297. The correlation value of first factor > the correlation value of second factor means that the learning difficulties variable is included in first factor. The correlation value of the learning anxiety variable with first factor is 0.329 and second factor is 0.628. The correlation value of first factor < the correlation value of second factor means that the learning anxiety variable is included in second factor group. The correlation value of the learning resource variable with first factor is 0.643 and second factor is 0.166. The correlation value of first factor > the correlation value of second factor, then the learning resource variable is included in first factor group.

The correlation value of the school facilities variable with first factor is 0.697 and second factor is 0.262. The correlation value of first factor > the correlation value of second factor means that the school facilities variable is included in first factor group. The correlation value of the learning approach variable with first factor is 0.599 and second factor is 0.296. The correlation value of first factor > the correlation value of second factor means that the learning approach variable is included in first factor group. The correlation value of the learning technique variable with first factor is 0.51 and second factor is 0.548. The correlation value of first factor < the correlation value of second factor, then the learning anxiety variable is included in second factor group.

The correlation value of the classroom variable with first factor is 0.502 and second factor is 0.474. The correlation value of first factor > the correlation value of second factor means that the classroom variable is included in first factor group. The correlation value of the subject matter variable with first factor is 0.635 and second factor is 0.271. The correlation value of first factor > the correlation value of second factor, then the subject matter variable is included in first factor group. The correlation value of the learning method variable with first factor is 0.617 and second factor is 0.306. The correlation value of first factor > the correlation value of second factor, then the learning method variable is included in first factor group .

The groups of factors and variables formed are as follows. First factor consists of the variables interest in learning, parental support, learning motivation, learning difficulties, learning resources, school facilities, learning approaches, classrooms, learning materials and learning methods. Second factor consists of the variables understanding concepts, self-confidence, learning models, learning anxiety, learning techniques.

The next output is the component transformation matrix. This output shows the correlation value between components. The output results are shown in the following table. The output component transformation matrix is shown in table 9 below.

Table 9. Component TransformationMatrix

| Component | 1 | 2 |
|---|---|---|
| 1 | 0.803 | 0.595 |
| 2 | -0.595 | 0.803 |

Based on the output results, information is obtained that components 1 and 2 have a correlation value of 0.803, where this correlation value is > 0.50. This means that the two factors formed can be concluded as suitable for summarizing the five variables analyzed.

### 3.2 Discussion

The findings from the principal component analysis reveal a multidimensional landscape that underpins students' perceptions of mathematics learning. The emergence of distinct factors aligns with prior research highlighting the interplay of cognitive, affective, and environmental elements in shaping academic experiences (Eccles and Wigfield 2020; Hui & Mahmud, 2023). Notably, the factor encompassing conceptual understanding and learning interest resonates with the well-established link between deep engagement with subject matter and intrinsic motivation (Demir, 2023). This understanding has become increasingly relevant in this global era, particularly as educational systems worldwide continue to adapt to post-pandemic learning environments and the integration of artificial intelligence in mathematics education (Irvine et al., 2023; Opesemowo, 2024)). The analysis revealed self-confidence as a distinct factor, underscoring its pivotal role in shaping mathematics perceptions. This finding not only resonates with extensive literature highlighting the profound impact of self-efficacy beliefs on academic performance and persistence (Clemente et al., 2024) but has gained renewed significance in recent years with the emergence of personalized learning technologies and adaptive mathematics platforms that aim to boost student confidence through tailored learning experiences (Engelbrecht & Borba, 2024; Dabingaya, 2022). The intersection of these factors with current educational trends, including the rise of digital mathematics learning tools and hybrid learning environments (Helsa et al., 2023), suggests that strategies aimed at bolstering students' self-confidence in their mathematical abilities should be prioritized, as a robust sense of self-efficacy continues to serve as a powerful catalyst for engagement and achievement in today's rapidly evolving educational landscape (Demir, 2023; Holenstein et al., 2022).

The emergence of a factor encompassing learning resources and school facilities accentuates the significance of the learning environment in shaping students' perceptions. This aligns with research emphasizing the profound influence of physical and material resources on academic outcomes (Maxwell, 2016). Well-equipped classrooms, libraries, and access to high-quality instructional materials contribute to a conducive atmosphere for learning, fostering engagement and facilitating comprehension. As such, educational stakeholders must prioritize the allocation of resources and ensure their equitable distribution across diverse learning contexts. Notably, the analysis revealed a distinct factor related to pedagogical approaches and teaching techniques, underscoring the pivotal role of instructional strategies in shaping students' experiences. This finding aligns with extensive literature on the impact of evidence-based teaching practices on student engagement, motivation, and achievement (Hattie, 2009; Kyriakides et al., 2013). Consequently, professional development initiatives aimed at equipping educators with effective pedagogical tools and strategies should be a priority, enabling them to create rich and engaging learning environments tailored to the diverse needs of their students.

Lastly, the analysis revealed a factor encompassing parental support, learning motivation, and academic anxiety, illuminating the intricate interplay between these elements. This finding aligns with research underscoring the influential role of familial support and emotional well-being in shaping academic trajectories (Khajehpour & Ghazvini, 2011; Putwain et al., 2018). Consequently, fostering strong home-school partnerships and implementing strategies to mitigate academic anxiety should be prioritized, as these efforts can bolster motivation and create a nurturing environment conducive to learning and growth.

## 4. CONCLUSION

This study aimed to map the multidimensional landscape of students' perceptions of mathematics learning by employing principal component analysis on a comprehensive survey instrument. The findings revealed five distinct underlying factors that shape students' perceptions: interest in learning, understanding of concepts, self-confidence, learning models, parental support, learning motivation, learning difficulties, learning anxiety, learning resources, school facilities, learning approaches, learning techniques, classrooms, subject matter and learning methods. The identification of these key components provides valuable insights into the complex interplay of cognitive, affective, and contextual factors that influence students' attitudes and experiences in mathematics learning. For instance, the results highlight the importance of fostering a strong sense of self-efficacy and confidence, as this factor was closely linked to higher levels of intrinsic motivation and lower perceptions of difficulty and anxiety. Additionally, the quality of teaching and the classroom environment emerged as a crucial factor, underscoring the pivotal role that educators play in shaping students' perceptions and attitudes towards mathematics.

The findings further suggest that interventions aimed at enhancing students' perceptions of mathematics learning should adopt a multifaceted approach, addressing not only the cognitive aspects of learning but also the affective and motivational dimensions. Strategies that promote the perceived relevance and usefulness of mathematics, create engaging and supportive learning environments, and build self-confidence and self-efficacy beliefs are likely to be more effective in fostering positive perceptions and improving student engagement and achievement in mathematics.Moreover, the study contributes to the growing body of literature on the application of multivariate statistical techniques, such as principal component analysis, in educational research. By leveraging the power of PCA, researchers can gain deeper insights into the underlying structure of complex phenomena, such as students' perceptions and attitudes, and develop targeted interventions and instructional strategies based on empirical evidence.While this study provides a solid foundation, future research could explore the generalizability of these findings across different educational settings, grade levels, and cultural contexts. Additionally, longitudinal studies could investigate how students' perceptions evolve over time and how these changes may influence their academic trajectories in mathematics. Furthermore, research could delve into the potential interactions between the identified factors and examine how they collectively shape students' overall perceptions and experiences in mathematics learning.

In conclusion, this study has shed light on the multidimensional nature of students' perceptions of mathematics learning and highlighted the importance of addressing both cognitive and affective factors in mathematics education. From the 15 components, 2 new factors were formed. First factor consists of the variables interest in learning, parental support, learning motivation, learning difficulties, learning resources, school facilities, learning approaches, classrooms, learning materials and learning methods. Second factor consists of the variables understanding concepts, self-confidence, learning models, learning anxiety, learning techniques. The findings have implications for educational practice, curriculum design, and professional development programs, emphasizing the need for a holistic approach that fosters positive perceptions, self-efficacy, and intrinsic motivation among students. By understanding and addressing the underlying factors shaping students' perceptions, educators can create more engaging and supportive learning environments, ultimately enhancing student achievement and cultivating a lifelong appreciation for mathematics.

**REFERENCES**

Ashcraft, M., & Ridley, K. S. (2005). Math anxiety and its cognitive consequences: A tutorial review. *Handbook of Mathematical Cognition*, 315–327.

Asli, A., & Iuliana, M. (2022). *"Techer's Attitudes Towards Teaching Mthematics" Scale: Factor Analysis*. https://doi.org/10.21125/inted.2022.2680

Beilock, S., & Maloney, E. (2015). Math Anxiety: A Factor in Math Achievement Not to Be Ignored. *Policy Insights from the Behavioral and Brain Sciences*, *2*, 4–12. https://doi.org/10.1177/2372732215601438

Bergmann, J., & Sams A. (2011). Flipped Your Classroom. In *Journal of Physics A: Mathematical and Theoretical* (Vol. 44, Issue 8). https://www.rcboe.org/cms/lib/GA01903614/Centricity/Domain/15451/Flip_Your_Classroom.pdf

Burusic, J., Babarović, T., & Velić, M. (2016). *School Effectiveness: An Overview of Conceptual, Methodological and Empirical Foundations* (pp. 5–26). https://doi.org/10.1007/978-3-319-29880-1_2

Carey, E., Hill, F., Devine, A., & Szűcs, D. (2017). *The Modified Abbreviated Math Anxiety Scale: A Valid and Reliable Instrument for Use with Children*. https://doi.org/10.17863/CAM.8377

Clemente, J. M., Kit Kilag, O. T., Ypon, A. Q., Groenewald, E. S., Adolph Groenewald, C., & Ubay, R. G. (2024). Enhancing Mathematics Self-Efficacy: Intervention Strategies and Effectiveness-A Systematic Review. *International Multidisciplinary Journal of Research for Innovation, Sustainability, and Excellence*, *1*(2). https://orcid.org/0009-0006-8919-4420

Creswell, J. W., & Creswell, J. D. (2021). Qualitative, quantitative and mixed methods research. In *Introducing English Language*. Sage Publications, Inc. https://doi.org/10.4324/9781315707181-60

Creswell, J. W., & Poth, W. C. (2018). Qualitative inquiry and research design: Choosing among five approaches (4th ed.). In *Вестник Росздравнадзора*. Sage Publications.

Dabingaya, M. (2022). Analyzing the Effectiveness of AI-Powered Adaptive Learning Platforms in Mathematics Education. *Interdisciplinary Journal Papier Human Review*, *3*, 1–7. https://doi.org/10.47667/ijphr.v3i1.226

Demir, F. (2023). The Relationship between Active Participation in Mathematics Classes and Motivational Regulation and Critical Thinking Disposition. *Turkish Journal of Mathematics*, *December 2023*. https://www.researchgate.net/profile/Furkan-Demir-4/publication/377335231_The_Relationship_between_Active_Participation_in_Mathematics_Classes_and_Motivational_Regulation_and_Critical_Thinking_Disposition/links/65a0e205af617b0d873ef6ee/The-Relationship-be

Di Martino, P., & Zan, R. (2009). "Me and maths": Towards a definition of attitude grounded on students' narratives. *Journal of Mathematics Teacher Education*, *13*, 27–48. https://doi.org/10.1007/s10857-009-9134-z

Dweck, C. S. (2006). The New Psychology of Success. In *Random House*.

Earthman, G. (2004). *Prioritization of 31 criteria for school building adequacy*.

Eccles, J., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, *61*, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Engelbrecht, J., & Borba, M. C. (2024). Recent developments in using digital technology in mathematics education. *ZDM - Mathematics Education*, *56*(2), 281–292. https://doi.org/10.1007/s11858-023-01530-2

Fennema, E., & Sherman, J. A. (1976). Fennema-Sherman Mathematics Attitudes Scales: Instruments Designed to Measure Attitudes toward the Learning of Mathematics by Females and Males. *Journal for Research in Mathematics Education*, *7*(5), 324–326. https://doi.org/10.2307/748467

Fitzpatrick, K., & May, S. (2022). *Critical Ethnography and Education: Theory, Methodology, and Ethics*. https://doi.org/10.4324/9781315208510

Forsey, M., Glance, D., Low, M., Glance, D., & Riley, M. (2013). The pedagogical foundations of massive open online courses, First Monday. *First Monday*, *18*. https://doi.org/10.5210/fm.v18i5.4350

Gunderson, E., Ramirez, G., Levine, S., & Beilock, S. (2011). The Role of Parents and Teachers in the Development of Gender-Related Math Attitudes. *Sex Roles*, *66*, 153–166. https://doi.org/10.1007/s11199-011-9996-2

Hattie, J. (2009). Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement. In *Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement*. https://doi.org/10.4324/9780203887332

Hayton, J., Allen, D., & Scarpello, V. (2004). Factor Retention Decisions in Exploratory Factor Analysis: A Tutorial on Parallel Analysis. *Organizational Research Methods*, *7*, 191–205. https://doi.org/10.1177/1094428104263675

Helsa, Y., Turmudi, & Juandi, D. (2023). TPACK-based hybrid learning model design for computational thinking skills achievement in mathematics. *Journal on Mathematics Education*, *14*(2 SE-Articles), 225–252. https://doi.org/10.22342/jme.v14i2.pp225-252

Holenstein, M., Bruckmaier, G., & Grob, A. (2022). How do self-efficacy and self-concept impact mathematical achievement? The case of mathematical modelling. *British Journal of Educational Psychology*, *92*(1), e12443. https://doi.org/https://doi.org/10.1111/bjep.12443

Hui, H. B., & Mahmud, M. S. (2023). Influence of game-based learning in mathematics education on the students' cognitive and affective domain: A systematic review. *Frontiers in Psychology*, *Volume 14*(2023). https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2023.1105806

Irvine, J., Telford, W., Alves, P., & Cloutier, A. (2023). *Teaching mathematics during COVID-19: Lessons learned and best practices*. *30*, Article 2.

Jollife, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *374*(2065). https://doi.org/10.1098/rsta.2015.0202

Kaur, B. (2008). Teaching and learning of mathematics: What really matters to teachers and students? *ZDM - International Journal on Mathematics Education*, *40*(6), 951–962. https://doi.org/10.1007/s11858-008-0128-6

Kaur, T., & Prendergast, M. (2021). Students' perceptions of mathematics writing and its impact on their enjoyment and self-confidence. *Teaching Mathematics and Its Applications: An International Journal of the IMA*, *41*. https://doi.org/10.1093/teamat/hrab008

Khajehpour, M., & Ghazvini, S. (2011). The role of parental involvement affect in children's academic performance. *Procedia - Social and Behavioral Sciences*, *15*, 1204–1208. https://doi.org/10.1016/j.sbspro.2011.03.263

Korpershoek, H., Harms, T., Boer, H., Kuijk, M., & Doolaard, S. (2014). *Effective classroom management strategies and classroom management programs for educational practice*.

Kosovich, J., Hulleman, C., Barron, K., Renninger, K., & Hidi, S. (2019). *The Cambridge Handbook of Motivation and Learning*. 713–738. https://doi.org/10.1017/9781316823279.030

Kyriakides, L., Christoforou, C., & Charalambous, C. (2013). What matters for student learning outcomes: A meta-analysis of studies exploring factors of effective teaching. *Teaching and Teacher Education*, *36*, 143–152. https://doi.org/10.1016/j.tate.2013.07.010

Lazowski, R. A., & Hulleman, C. S. (2016). Motivation Interventions in Education: A Meta-Analytic Review. *Review of Educational Research*, *86*(2), 602–640. https://doi.org/10.3102/0034654315617832

Maxwell, L. (2016). School building condition, social climate, student attendance and academic achievement: A mediation model. *Journal of Environmental Psychology*, *46*. https://doi.org/10.1016/j.jenvp.2016.04.009

Mohamed, L., & Waheed, H. (2011). *Secondary Students' Attitude towards Mathematics in a Selected School of Maldives*. *1*.

Opesemowo, O. (2024). *Artificial Intelligence in Mathematics Education: The Pros and Cons* (pp. 1–18). https://doi.org/10.4018/978-1-6684-7366-5.ch084

Putwain, D., Becker, S., Symes, W., & Pekrun, R. (2017). Reciprocal relations between students' academic enjoyment, boredom, and achievement over time. *Learning and Instruction*, *54*.

https://doi.org/10.1016/j.learninstruc.2017.08.004

Putwain, D., Pekrun, R., Nicholson, L., Symes, W., Becker, S., & Marsh, H. (2018). Control-Value Appraisals, Enjoyment, and Boredom in Mathematics: A Longitudinal Latent Interaction Analysis. *American Educational Research Journal*, *55*, 000283121878668. https://doi.org/10.3102/0002831218786689

Quintana, C., Reiser, B., Davis, E., Krajcik, J., Fretz, E., Duncan, R., Kyza, E., Edelson, D., & Soloway, E. (2004). A Scaffolding Design Framework for Software to Support Science Inquiry. *Journal of the Learning Sciences*, *13*, 337–386. https://doi.org/10.1207/s15327809jls1303_4

Rittle-Johnson, B., & Schneider, M. (2015). *Developing Conceptual and Procedural Knowledge of Mathematics* (pp. 1102–1118). https://doi.org/10.1093/oxfordhb/9780199642342.013.014

Skaalvik, E. M., Federici, R. A., & Klassen, R. M. (2015). Mathematics achievement and self-efficacy: Relations with motivation for mathematics. *International Journal of Educational Research*, *72*, 129–136. https://doi.org/https://doi.org/10.1016/j.ijer.2015.06.008

Stankov, L., Morony, S., & Lee, Y. P. (2014). Confidence: The best non-cognitive predictor of academic achievement? *Educational Psychology*, *34*(1), 9–28. https://doi.org/10.1080/01443410.2013.814194

Tabachnick, B. G., & Fidell, L. S. (2013). Review of Using Multivariate Statistics. In *Contemporary Psychology: A Journal of Reviews*. Pearson Education. https://doi.org/10.1037/022267

Tapia, M., & Marsh, G. E. (2004). An Instrument to Measure Mathematics Attitudes. *Academic Exchange Quarterly*, *8*, 16–22. https://api.semanticscholar.org/CorpusID:141284071

Wang, M.-T., & Sheikh-Khalil, S. (2013). Does Parental Involvement Matter for Student Achievement and Mental Health in High School? *Child Development*, *85*. https://doi.org/10.1111/cdev.12153

Weng, T.-S. (2017). The Importance of Mathematics and Science Education in the Context of Digital Technology on Industrial Innovation. *Research Journal of Applied Sciences, Engineering and Technology*, *14*(11), 418–426. https://doi.org/10.19026/rjaset.14.5142

Wheeldon, J. (2010). Mapping Mixed Methods Research: Methods, Measures, and Meaning. *Journal of Mixed Methods Research*, *4*, 87–102. https://doi.org/10.1177/1558689809358755

Xie, K., Tosto, G., Chen, S.-B., & Vongkulluksn, V. (2018). A systematic review of design and technology components of educational digital resources. *Computers & Education*, *127*, 90–106. https://doi.org/10.1016/j.compedu.2018.08.011

Zan, R., & Di Martino, P. (2007). Attitude toward mathematics: Overcoming the positive/negative dichotomy. *Montana Council of Teachers of Mathematics*, *3*, 157–168.