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Unveiling College Student Preferences: Integrating Numerical and Factor Analysis in Understanding Choices for Mathematics Majors

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ABSTRACT

Purpose of the study: This study explores the use of numerical analysis to understand the factors influencing students in selecting mathematics majors.

Methodology: Data were collected through structured interviews from 150 students in two different universities using stratified random sampling technique. Analysis was conducted using Principal Component Analysis (PCA) and Varimax rotation to identify the main dimensions that influence student preferences. Numerical analysis helped to group variables into relevant factors based on loading values. In addition, simulations and numerical validation techniques were conducted, from the eigenvalues and loading factors obtained from Principal Component Analysis (PCA) to test their stability.

Main Findings: Factors that influence students in choosing Mathematics Major consist of 19 variables which are grouped into 5 factors, namely: the first factor is privileges and facilities with an eigenvalue of 4.088%, the second factor is the lecture building and social factors with an eigenvalue of 2.431%, the third factor is the promotion factor with an eigenvalue of 1.743%, the fourth factor is the job factor with an eigenvalue of 1.351%, the fifth factor is the comfort factor with an eigenvalue of 1.148%.

Novelty/Originality of this study: These findings provide new insights for educational institutions in designing effective promotional strategies and developing relevant curricula to increase the attractiveness of mathematics majors. The novelty of this study lies in the application of factor analysis to map students' specific reasons, which has rarely been done before in the context of higher education.

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1. INTRODUCTION

Higher education plays an important role in shaping individual competencies to face global challenges [1], [2]. The choice of major by students is one of the important decisions that affect the direction of their careers and their contribution to society. In this context, the mathematics major, especially in universities, has its own appeal because of its relevance to various fields such as technology, economics, and science [3]-[5]. However, not all students are interested in choosing mathematics as their major, even though its potential is enormous in the era of data and digitalization [6]. Therefore, a deeper understanding is needed of the factors that influence students' choices in choosing this major.

Mathematics, as a basic science, does not only focus on calculating numbers but also has wide applications in various applied fields [7]-[9]. Mathematics majors are often considered challenging because they require high analytical skills and logical thinking [10], [11]. However, this field offers great opportunities in careers such as data analysis, technology development, and scientific innovation [12]-[14]. This shows the importance of understanding the motivations and barriers felt by students before choosing this major. A comprehensive analysis of these factors can provide new insights to increase the attractiveness of mathematics majors.

Factors that influence the choice of major involve various aspects, ranging from personal interests, environmental influences, to future career prospects [15]-[17]. In this case, each individual has different considerations based on experience, family support, and access to information [18], [19]. Previous studies have shown that the choice of major is often influenced by perceptions of the difficulties and opportunities offered [20], [21]. However, for mathematics majors, further research is needed to identify specific patterns that can be used as guidelines for educational promotion strategies.

Factor analysis is a statistical method used to identify the main variables that are interrelated in a phenomenon [22]-[24]. This method is very relevant to explore data related to students' decisions in choosing a mathematics major. By using factor analysis, the main dimensions that influence student preferences can be found, such as academic motivation, social support, and perceptions of career prospects [25], [26]. This method allows for more effective data-based decision-making in the development of majors. Therefore, the application of factor analysis is a strategic approach in this study.

Factor analysis is a strategic approach to identify key variables that influence student decisions [27]. To increase the validity of the research results, numerical analysis is used as a supporting tool. Numerical analysis allows complex data processing, including validation of Principal Component Analysis (PCA) results, and provides additional insights through simulation and sensitivity testing [28], [29]. This approach not only improves the accuracy of the results but also enriches the analysis with a data-driven perspective. In this study, the application of numerical analysis provides a stronger framework for understanding student preferences. This integration aims to produce findings that are relevant both locally and globally, supporting the development of more effective and highly competitive mathematics education strategies.

Numerical analysis is a cornerstone of modern scientific computation, enabling researchers to solve complex problems with precision and efficiency. In educational research, it offers powerful tools for validating statistical models and ensuring data reliability. This study investigates student preferences for mathematics majors through the lens of numerical analysis, emphasizing its application in validating PCA results and understanding factor structures.

The main focus of this study is to explore the factors that influence students in choosing a mathematics major, both in local and global contexts. Locally, the results of this study can help universities understand student needs and formulate more relevant educational policies [30]-[32]. Globally, these findings can provide insights for other educational institutions to increase the attractiveness of mathematics as a field of study [33], [34]. Thus, this study has broad benefits, ranging from the development of local educational programs to contributing to improving the quality of mathematics education globally [35].

This research also contributes in a broader context, namely providing insight to the community and policy makers regarding the importance of understanding the factors in choosing a major. On a global scale, this issue is relevant because mathematics education is a major foundation for progress in science and technology [36]-[38]. The findings of this study can be applied in various universities or other educational institutions that face similar challenges [39]-[41]. By understanding the needs and motivations of students, strategic steps can be designed to increase interest in applied mathematics.

Gap analysis between previous studies conducted by Shrestha [42] namely previous studies used factor analysis as a tool to analyze surveys in general, focusing on variable grouping techniques to identify hidden patterns in respondent data. However, the current study is more specific, applying factor analysis to map student preferences in choosing a mathematics major. The gap that emerged lies in the applied focus: previous studies only highlighted the potential of factor analysis technically, while the current study explores the specific reasons behind academic decisions, providing more contextual and relevant insights into the development of educational strategies.

Gap analysis between previous studies conducted by Messerle et al., [43] focusing on the use of numerical analysis in the processing of medical-biological waste and biomass fuel through plasma-chemical processes, where experiments and numerical models are used to understand the efficiency and impact of these processing techniques. Meanwhile, the current study combines numerical and factor analysis to identify students' preferences in choosing a mathematics major, with a statistical approach that focuses more on psychological and social aspects. Although both rely on numerical analysis to explore complex phenomena, previous studies are more focused on the application of technology in waste processing, while the current study focuses on factors that influence students' educational decisions. The main difference lies in the object of research—one deals with waste treatment technology and the other with individual behavior in education.

This study has the novelty of applying factor analysis to map students' preferences and reasons for choosing mathematics majors, an approach that is rarely used in the context of higher education. In addition, the urgency of this study lies in the importance of understanding students' motivations to help educational institutions design more effective promotion strategies and curricula that are in line with students' needs and expectations. By utilizing this approach, the results of the study can make a significant contribution to increasing the attractiveness of mathematics majors, which are often less popular than other disciplines.

Based on the description above, this study aims to explore the factors that influence students in choosing a mathematics major through the application of factor analysis. This study is not only beneficial for the internal development of the university, but also contributes to the development of educational strategies at the national and global levels. It is hoped that this study can be a basis for improving policies and promoting mathematics education in the future. Thus, the results of this study are expected to provide broad benefits, both locally and globally.

2. RESEARCH METHOD

2.1. Type of Research

This research is included in the category of quantitative research with a descriptive-analytical approach. Descriptive research aims to describe students' preferences in choosing a mathematics major based on predetermined variables [44]. Meanwhile, the analytical approach is carried out by applying factor analysis to identify the main dimensions that influence students' decisions [45].

As part of quantitative research, numerical analysis is used to strengthen the results obtained from Principal Component Analysis (PCA) [46], [47]. This approach allows for big data processing and model validity testing, ensuring more accurate results. By combining descriptive and numerical analysis, this study provides a comprehensive framework for understanding students' preferences in depth.

2.2. Population and Sample

The population used in this study consisted of students of the Mathematics Department of the Faculty of Science and Technology at a University in Sumatera Island, Indonesia, and students of the Mathematics Department of the Faculty of Science at a University in Lagos City, Nigeria. This population includes all active students registered at both universities in the 2022/2023 academic year.

The sample is a portion of the population [48], [49], the number of which is limited to 75 students from each university. so that the total sample taken from both universities is 150 students. In this study, the sampling technique used is stratified random sampling [50], [51]. The sample selection is done randomly from each stratum to ensure that each student has an equal chance of being selected [52], [53]. The sample selection is based on the list of active students in the Mathematics department at both universities. By using the stratified random sampling technique, this study can ensure that the samples taken represent the population at both universities and consider the differences between strata based on the country of origin of the university.

2.3. Data Collection Instruments and Techniques

In this study, the data collection technique used was structured interviews. Interviews were conducted with students who happened to meet the researcher and met the criteria for the characteristics of the sample that had been determined. Students who met these criteria would be selected as informants to be interviewed. The interview guidelines used focused on questions about the reasons why students initially chose the Mathematics Department. These guidelines were designed to gain a deeper understanding of the factors that influenced their decisions in choosing the department. The indicators used by researchers to determine the factors that influence students in choosing the mathematics department can be seen in the following table:

Table 1. List of indicators in selecting a Mathematics major

No.	Aspects	Indicator
1.	Promotion and Socialization	a) The Mathematics Department can be known through advertisements and mass media. b) Promotion is packaged creatively and attractively with complete information about the Mathematics Department. c) Socialization of the Mathematics Department carried out in schools. d) Socialization from alumni. e) Accreditation of the Mathematics Department.
2.	Location and Lecture Building	a) Middle Eastern-style Mathematics department lecture building.

		b) Spacious, comfortable, and clean Mathematics department lecture building. c) Spacious, comfortable, beautiful, and shady Mathematics department lecture location because of the many trees. d) Easily accessible Mathematics department lecture location. e) Mathematics department lecture location far from the hustle and bustle of the city.
3.	Facility	a) The Mathematics Department has an adequate Computer Lab. b) The Mathematics Department has a department library. c) Lecturers who are experts and competent in the field of Mathematics studies.
4.	Interest	a) Enjoy learning Mathematics. b) Mathematics can be applied in various fields of science. c) Mathematics Studies of the Mathematics Department of the Faculty of Science and Technology are integrated with Technology.
5.	Work	a) The job prospects of the Mathematics Study program have good job opportunities. b) Graduates of the Mathematics major can be accepted in various workplaces
6.	Social and economic	a) Invitation from friends and relatives. b) Parental advice. c) Parental background d) Not graduating from other majors e) Cheap tuition fees in the Mathematics major. f) Rarely do criminal acts such as brawls occur.

2.4. Data Analysis Procedure

The data analysis procedure in this study begins with determining the variables to be analyzed, namely selecting variables that are relevant to the research objectives [54]. After that, a correlation matrix calculation is carried out using the Bartlett Test of Sphericity to test the suitability of the data, as well as the Measure of Sampling Adequacy (MSA) measurement to assess the suitability of the data in factor analysis [55], [56]. Furthermore, the factor extraction process is carried out using the Principal Component Analysis (PCA) method, which aims to reduce the number of variables by combining correlated variables into main components [57]. Then, the number of most influential factors is determined by looking at the eigenvalue value which is greater than 1, which indicates that the factor makes a significant contribution to data variability. After the number of factors is determined, factor rotation is carried out using the Varimax method to clarify the position of the variables in each factor, facilitate interpretation, and increase separation between factors. Finally, the factors obtained are analyzed and interpreted to understand the relationship between the variables contained in each factor, thus producing a deeper understanding of the phenomenon being studied.

Numerical analysis was used to calculate the correlation matrix and ensure the data met the PCA requirements through Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity. This process determines the suitability of the data for factor analysis. Numerical techniques were applied to validate the factor extraction results by calculating the eigenvalues and variable contributions to the factors [58]. Numerical simulations were conducted to test the stability of the eigenvalues by iteratively modifying the input data [59]. Varimax rotation was applied to maximize the interpretation of the PCA results. Numerical analysis helped to group the variables into relevant factors based on the loading values. To validate the robustness of the model, numerical analysis was conducted by simulating small changes in the data. The simulation results showed that insignificant changes did not affect the factor structure, ensuring the stability of the model. The analysis process is carried out using statistical software such as SPSS and MATLAB. MATLAB is used specifically for numerical simulations, which allows for a more in-depth analysis of the sensitivity and validity of the data [60], [61]. The results of the numerical analysis are presented in the form of eigenvalue tables, variance contributions, and Scree Plot graphs to support visual interpretation. The simulation provides additional insight into the accuracy of the model, ensuring that each factor has a significant contribution to student preferences.

Numerical techniques were applied to validate eigenvalues and factor structures, including the use of QR decomposition for eigenvalue calculation and Monte Carlo simulations to test the stability of eigenvalues and factor contributions under random noise. Rotational optimization through Varimax rotation was also conducted to improve the clarity of factor loadings. The Monte Carlo simulations involved 1,000 iterations, where Gaussian noise with a standard deviation of 5% of the mean values was added to the input data. This approach ensured the robustness of the PCA results and factor assignments.

2.5. Research Procedures

This study began with the identification of the problem and objectives, followed by the selection of a population consisting of Mathematics Department students at two different universities, with samples taken using stratified random sampling techniques. Data were collected through structured interviews with students who met the sample criteria, using interview guidelines that focused on major selection factors, such as promotion, facilities, location, interests, jobs, and socio-economic factors. After the data was collected, a suitability test was carried out using the Bartlett Test of Sphericity and Measure of Sampling Adequacy (MSA), then the analysis was carried out using the Principal Component Analysis (PCA) method for factor extraction, followed by Varimax rotation to clarify the relationship between variables. Significant factors were selected based on eigenvalues greater than 1 and interpreted to provide a deep understanding of the factors that influence major selection. The results of the study were then compiled in a report that included findings and conclusions. The procedure for this study can be seen in the following figure:

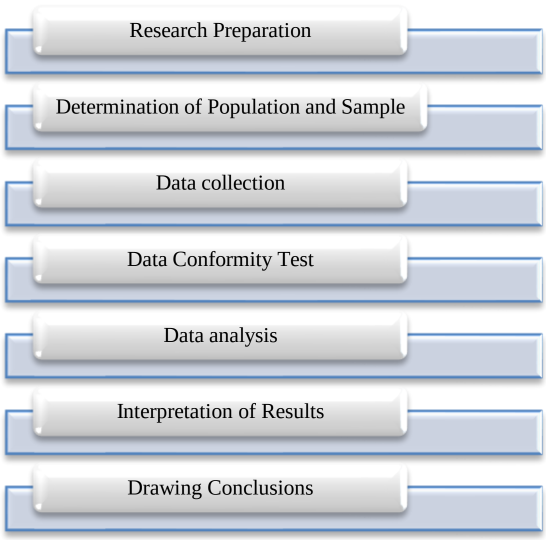

Figure 1. Research Procedure

3. RESULTS AND DISCUSSION

Factors that influence students in choosing Mathematics Majors can be identified by using factor analysis method. The stages of factor analysis are as follows:

1. Test the correlation and feasibility of a variable.

This stage tests the correlation of the variables that have been defined using the Bartleet's Test of Sphericity and the Kaiser Meyer Olkin Measure of Sampling Adequacy (MSA). The Bartlet's Test and the MSA test are conducted to assess the feasibility of a variable to be analyzed using factor analysis. With the following criteria:

a. Bartlett's Test (Bartlett's Test of Sphericity)

Barlett's test in factor analysis is to test the correlation between variables because the desired result in factor analysis is a high correlation between variables, having a high correlation if the calculated Barlett value > Barlett table, or p-value (sig) $\alpha = (0.05)$, then it shows a high correlation value between variables and the process can be continued. The hypothesis for significance is, H_0 = No correlation H_1 = Has correlation and adequate sample for further analysis. The criteria for seeing significance are Sig Value > $\alpha = (0.05)$ then Ho is accepted, Sig < $\alpha = (0.05)$ then H_0 is rejected.

Table 2. KMO Values and Bartlett's Test of Sphericity

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**.625**
Bartlett's Test of Sphericity	**Approx. Chi-Square**	**549.964**
	ds	**276**
	Sig.	**.000**

Table 2. KMO and Bartleet's Test of Sphericity show that sig < α = 0.05 where the sig value in the table is 0.000 < 0.05. So the variables are correlated and can be processed further.

b. Measure of Sampling Adequancy (MSA) Test
The MSA test is a test used to measure homogeneity between variables and filter between variables so that only qualified variables can be processed further. Where the MSA value is 0.5 - 1.0. With the criteria, namely MSA = 1, the variable can be predicted without error by other variables. MSA = 0.5, the variable can be predicted and can be analyzed further. MSA = variable cannot be predicted and is not analyzed further and is removed from other variables. As seen in Table 2, the KMO value and Bartleet's Test of Sphericity = 0.625 so that the factor analysis process can be continued because it meets the requirements where the calculated KMO value > KMO table, namely 0.625 > 0.5. The criteria for seeing significance are: Sig value < α = (0.05) then H_0 is accepted, Sig > α = (0.05) then H_0 is rejected.

In the image matrices anti image correlation section, the variables formed after the MSA test are as follows:

Table 3. Anti Image Matrices Correlation values after the X19 variable was removed from the MSA test.

Variables	MSA Value	Minimum standard value
Mathematics majors can be known through advertisements and mass media (X_1)	0.565	0.5
The promotion is packaged creatively and attractively and contains complete information about the mathematics department (X_2)	0.678	0.5
Socialization from alumni (X_4)	0.527	0.5
Accreditation of Mathematics Department (X_5)	0.711	0.5
The Mathematics Department lecture building is spacious, comfortable and clean (X_7)	0.649	0.5
The Mathematics Department's lecture location is spacious, comfortable, beautiful and shady because of the many trees (X_8)	0.733	0.5
Easy to reach location of Mathematics Department lectures (X_9)	0.778	0.5
The location of the Mathematics study program is far from the hustle and bustle of the city (X_{10})	0.526	0.5
The Mathematics Department has an adequate Computer Lab (X_{11})	0.782	0.5
The Mathematics Department has a departmental library (X_{12})	0.782	0.5
Expert and competent teachers in the field of Mathematics studies (X_{13})	0.804	0.5
Mathematics can be applied in various fields of science (X_{15})	0.772	0.5
Mathematics Study Department of Mathematics Faculty of Science and Technology is integrated with Technology science (X_{16})	0.804	0.5
The job prospects for the Mathematics Study Program have good job opportunities (X_{17})	0.762	0.5
Mathematics graduates can be accepted in various workplaces (X_{18})	0.732	0.5
The background of the parents is a science graduate (X_{21})	0.626	0.5
Cheap education costs (X_{23})	0.615	0.5
Crimes such as brawls rarely occur (X_{24})	0.588	0.5

From the MSA Test table 3 MSA Test shows that there are several variables that have MSA values below 0.5, so each variable must be removed from the next MSA test. After the variables that do not meet the MSA requirements are removed one by one, a variable is formed that has a loading value > 0.5.

2. Factoring or extraction process

The factoring or extraction process is the process of separating variables that meet the correlation of the MSA value, where a variable is said to be correlated if the MSA value is greater than 0.5. The method used is Principal Components Analysis (PCA). The number of variables to be extracted can be seen in table 10 of the contribution of the extracted variables.

Table 4. Contribution of Extraction Result Variables

Communalities

	Initial	**Extraction**
X_1	1.000	.518
X_2	1.000	.628
X_4	1.000	.573
X_5	1.000	.514
X_7	1.000	.637
X_8	1.000	.568
X_9	1.000	.411
X_{10}	1.000	.775
X_{11}	1.000	.640
X_{12}	1.000	.633
X_{13}	1.000	.590
X_{15}	1.000	.584
X_{16}	1.000	.740
X_{17}	1.000	.699
X_{18}	1.000	.788
X_{21}	1.000	.450
X_{23}	1.000	.462
X_{24}	1.000	.550

Extracyion Method: Principal Component Analysis.

Table 4 contribution of extracted variables shows the value of the variables to the formed factors. The greater the contribution of a variable, the closer the relationship with the formed factors. Furthermore, Table 5 will show more specific extraction results using the Principal Components Analysis (PCA) method, seen in the Eigenvalue value greater than or equal to 1.0. The specific results of PCA extraction are shown in Table 5 PCA Extraction Results as follows:

Table 5. PCA Extraction Results

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	4.088	22.712	22.712
2	2.431	13.507	36.220
3	1.743	9.685	45.904
4	1.351	7.503	53.407
5	1.148	6.378	59.786
6	.966	5.367	65.153
7	.901	5.004	70.157
8	.857	4.763	74.920
9	.759	4.219	79.139
10	.623	3.464	82.603
11	.582	3.232	85.834
12	.544	3.021	88.855
13	.459	2.548	91.403
14	.366	2.031	93.434
15	.360	1.998	95.431
16	.313	1.737	97.168
17	.272	1.510	98.678
18	.238	1.322	100.000

Extraction Method: Principal Component Analysis.

In Table 5 PCA Extraction Results is a table of extraction results from a number of variables that influence students in choosing a Mathematics major. The total variables that have a correlation are 18 variables, then in Table 6 the total extraction results, the number of extraction result factors will be seen.

Table 6. Number of factors resulting from extraction (PCA)

Extraction Sums of Squared Loading		
Total	% of Variance	Cumulative %
4.088	22.712	22.712
2.431	13.507	36.220
1.743	9.685	45.905
1.351	7.503	53.407
1.148	6.378	59.786

From 18 extracted variables, 5 factors were formed as seen in Table 6 Number of Extraction Result Factors (PCA), from 5 factors formed, all factors have eigenvalues > 1, for example in the total factor column 1 = 4.088 > 1. In addition to the total variance table, there is also a graph that explains the basis of calculation in determining the number of factors, seen in the Scree Plot graph. The shape of the Scree Plot graph that corresponds can be seen in Figure 1 Scree Plot as follows:

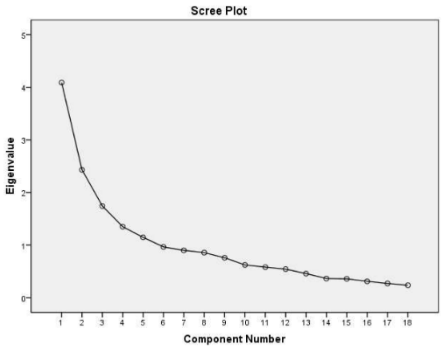

Figure 1. Scree plot of factor extraction results

In Figure 1 Scree Plot it can be seen that point 1 to point 2 shows a sharp difference in distance, this indicates that the correlation between factor 1 and factor 2 is much different, for point 2 to point 3 there is still a difference, for the next point it can be seen that the difference in distance is not much different until point 5. So these 5 factors can explain the 16 original variables.

3. Factor Rotation

The extracted variables will be rotated because usually the placement of variables is not right or there are still variables that do not match the factors. The rotation process is carried out on variables that pass the MSA test. The component matrix can determine the contribution of variables to the factors formed. The results of the rotation, show that all variables have factor groups, variable X_{23} which was previously unclear in which factor, after rotating the variable X_{23} is in factor group 2 which has the largest loading value, namely (0.669). Factors can be grouped according to the variables that form them, as can be seen in Table 7 as follows:

Table 7. Group of Rotation Result Factors

Variables	Factor Group				
	1	2	3	4	5
X_1			**3**		
X_2			**3**		
X_4		**2**			
X_5			**3**		
X_7		**2**			
X_8		**2**			
X_9			**3**		

X_{10}					**5**
X_{11}	**1**				
X_{12}	**1**				
X_{13}	**1**				
X_{15}	**1**				
X_{16}	**1**				
X_{17}				**4**	
X_{18}				**4**	
X_{21}		**2**			
X_{23}		**2**			
X_{24}					**5**

From Table 7 it can be seen that all factors have forming variables where: factor 1 has 5 forming variables, factor 2 has 5 forming variables, factor 3 has 4 forming variables, factor 4 has 2 forming variables, factor 5 has 2 forming variables.

Loading value identifies the correlation between variables and the factors formed. The higher the loading value means the closer the relationship between the variables and the factors. From Table 7, the group of rotation factors shows that all variables form a factor based on their largest loading value, so that the factors are interpreted in Table 8, the results of the variable interpretation as follows:

Table 8. Results of variable interpretation

No.	Variable	Factor	Eigen Values	Loading Faktor	% Variance	Cumulative %
1	X_{11}	Privileges and facilities factors	4.088	0.750	22.712	22.712
2	X_{12}			0.776		
3	X_{13}			0.534		
4	X_{15}			0.692		
5	X_{16}			0.732		
6	X_4	Location and social factors	2.431	0.464	13.507	36.220
7	X_7			0.721		
8	X_8			0.629		
9	X_{21}			0.567		
10	X_{23}			0.669		
11	X_1	Promotion factors	1.743	0.688	9.685	45.904
12	X_2			0.750		
13	X_5			0.513		
14	X_9			0.596		
15	X_{17}	Job factors	1.351	0.726	7.503	53.407
16	X_{18}			0.864		
17	X_{10}	Comfort factor	1.148	0.780	6.378	59.786
18	X_{24}			0.573		

Based on Table 8, the factors formed are:

$F_1 = 0{,}750X_{11} + 0{,}776X_{12} + 0{,}534\ X_{13} + 0{,}692X_{15} + 0{,}732X_{16}$

$F_2 = 0{,}468X_4 + 0{,}721X_7 + 0{,}629X_8 + 0{,}567\ X_{21} + 0{,}669\ X_{23}$

$F_3 = 0{,}688X_1 + 0{,}750X_2 + 0{,}513X_5 + 0{,}596X_9$

$F_4 = 0{,}726X_{17} + 0{,}864X_{18}$

$F_5 = 0{,}780X_{10} + 0{,}573X_{24}$

Each variable correlates with the formed factor, this can be seen from the way of squaring the correlation value in Table 8 based on the equation, for example the Mathematics Department variable can be known through advertisements and mass media (X_1) is:

$X_1 = h_i^2 + \Psi_i$

$= I_{i1}^2 + I_{i2}^2 + \ldots + I_{im}^2$

$= (-0.030)^2 + (0.434)^2 + (0.570)^2 + (-0.053)^2 + (0.032)^2$

$= 0.0009 + 0.188356 + 0.3249 + 0.002809 + 0.001024$

$= 0.517989$. The proven extraction value can be seen in the extraction table.

Based on Table 8 Component Matrix after Rotation, there is Figure 2 which is the component or number of variable members in the factor. Figure 2 is a picture of the location and components of the variables in the factor so this picture is a means to clarify the location of a variable so that it is easier to know the location of the variable in the factor.

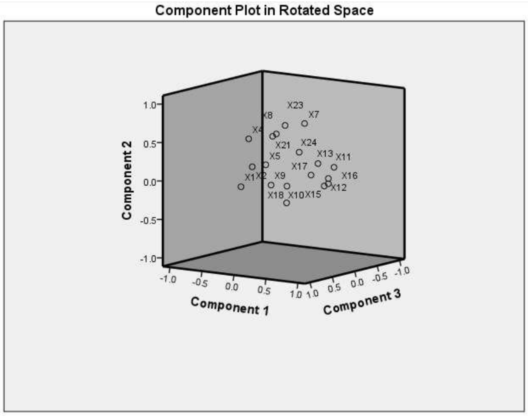

Figure 2. Component Plot In Rotated Space

From Figure 2 Component Plot In Rotated Space it can be seen that the components consist of variables that form factors.

The variables that have been grouped are given names, where the name of the factor depends on the variables that form it. So that the naming is subjective and there are no definite provisions regarding the naming. The naming of factors is explained as follows:

a. Factor 1, namely Privileges and Facilities

The first factor is named specialty because the representative variables consist of X_{11} = The Mathematics Department has an adequate Computer Lab, X_{12} = The Mathematics Department has a department library, X_{13} = The Mathematics Department has expert and competent teachers, X_{15} = Mathematics can be applied in various fields of science, X_{16} = Mathematics Studies of the Mathematics Department of the Faculty of Science and Technology are integrated with the science of Technology. The specialty factor is able to explain the diversity of variance of = 22.712%. When viewed from the loading value, the variable that has the most influence on the specialty factor is the variable X_{12} = The Mathematics Department has a department library with a correlation value of = 0.776 because it has a loading value then the variable X_{11} = 0,750, X_{16} = 0,732, X_{15} = 0,692, X_{13} = 0,534. The academic interest factor underlines the importance of students' active involvement in interdisciplinary programs. For example, the integration of mathematics with technology, science, and economics can increase the attractiveness of this major. Universities need to provide research opportunities for students, so that they can experience the direct relevance of mathematics in solving real-world problems [62].

The Facility Factor is one of the factors that influence students in choosing the Mathematics Department because the facility factor has the variable X_{12} which is a variable that has a high loading value. Variable X_{12} = the Mathematics Department has a department library. The facility dimension shows that students value infrastructure that supports the teaching and learning process. Universities that are able to provide international standard facilities, such as laboratories with the latest technology and comfortable study rooms, will have a competitive advantage [63]. Investment in these facilities not only supports the academic process but also creates an attractive environment for global students [64].

b. Factor 2, namely Lecture Buildings and Social

The Lecture Building and Social factors are the second factors that can influence students in choosing Mathematics majors. Because this factor has a variance diversity of = 13.507%. The Lecture Building and Social factors consist of variables X_4, X_7, X_8, X_{21}, X_{23}. variable X_7 has a loading value = 0,738 and variables X_8 has a loading value = 0.616, variable X_{21} = 0,475, variable X_{21} = 0,648. The variables that have a high correlation with the Lecture Building and Social factors are the variables X_7 because it has a loading value = 0.738. The comfort factor and cleanliness of the building greatly influence the selection of the Mathematics Department. The Lecture Building and Social factors are factors that influence students in choosing the Mathematics Department because it has a spacious, comfortable, and clean Mathematics Department lecture building, so prospective students are interested in choosing the Mathematics Department. A spacious, comfortable, and clean lecture building is one of the attractions. Comfort is one of the factors considered in choosing a major because why choose a major if it is not comfortable to do it.

c. Factor 3 is promotion

The third factor is the promotion factor because it has an eigenvalue of 1.743 and a variance of = 9.685, this factor consists of the variables X_1 = 0,688, X_2 = 0,750, X_5 = 0,513, X_9 = 0,596. The variable that has the most influence on the promotion factor is the variable X_2 = 0,750 because it has the highest loading value compared to other variables in the promotion factor. The promotion factor is one of the factors that influences students in choosing the Mathematics Department because the promotion factor consists of variables X_2 = Promotion is packaged creatively and attractively with complete information about the Mathematics Department. Promotion factors influence the selection of the Mathematics Department because promotion factors are factors that convey the existence of a Department. Promotion factors can introduce the existence of the Mathematics Department in full, which is packaged creatively and attractively. So that prospective students can get to know the Mathematics Department and know the existence of the Mathematics Department, because without knowing the existence of the Mathematics Department, prospective students will not choose the Mathematics Department. So the promotion factor is one of the factors that influences students in choosing a mathematics department. The dimensions of promotion and socialization provide a strategic view of the importance of targeted communication in attracting the attention of prospective students. Digital campaigns that focus on the power of mathematics as a "universal language" can help build positive perceptions in the wider community [65]. In addition, alumni who are successful in their careers can be involved as ambassadors to motivate prospective students with their real stories [66].

d. Factor 4 is work

The fourth factor is the job factor because this factor has an eigenvalue = 1.351 and a variance value = 7.503. Job factors consist of variables X_{17} = 0,726, and variables X_{18} = 0,864. The variable that has a high correlation value is X18 = 0.864. The job factor is a factor that influences students in choosing a Mathematics major because students will definitely look for a major that has good job prospects. The job prospect dimension emphasizes the need to bridge the gap between the academic world and the industrial world. Universities can expand partnerships with technology companies, financial institutions, and research organizations to create internship programs and career guidance [67], [68]. By providing a clear picture of job prospects, such as opportunities to become data analysts, researchers, or algorithm developers, students can feel more confident in choosing this major [69].

e. Factor 5 is comfort

The comfort factor is one of the factors that influences students in choosing the Mathematics Department because it has an eigenvalue = 1.148 and variance = 6.378%. The convenience factor consists of variables X_{10} = 0,780, X_{24} = 0,573. Where are the variables X_{24} = there are rarely any criminal acts such as brawls, this factor is something that influences students in choosing the Mathematics Department because it is rare to hear of criminal acts and it is almost never heard of Mathematics Department students committing criminal acts, this is one of the factors that prospective students consider in choosing a department.

The results showed that factors such as facility privileges, job prospects, and promotions have a significant influence on student preferences. In addition, numerical analysis was applied to validate the eigenvalues and check the stability of the PCA results. Simulations showed that small changes in the input data did not significantly affect the final results, confirming the reliability of the resulting model. The results of the numerical analysis to validate the eigenvalues and check the stability of the PCA results can be seen in the table below:

Table 9. Numerical Analysis Results to Validate Eigenvalues and Check the Stability of PCA Results

Factor	Main Variable	Eigenvalues	Percentage Variance (%)
Facility Features	Adequate computer laboratory (X_{11}) Departmental Library (X_{12}) Expert and competent teachers (X_{13}) Integration of technology in learning (X_{16})	4.088	22.712
Promotion	Creative and informative promotions (X_2) Information through advertising and media (X_1)	1.743	9.685
Location and Social	Comfortable and clean building (X_7) Strategic location and easy to reach (X_8)	2.431	13.507
Work	Good job prospects (x_{17})	1.351	7.503

	Accepted in various workplaces (X_{18})		
Comfort	Safe environment without crime (X_{24})	1.148	6.378

The table illustrates five main factors that influence students' preferences in choosing a mathematics major, namely the privilege of facilities, promotion, location and social, job prospects, and comfort. The privilege of facilities factor has the largest contribution in explaining data variance with an eigenvalue of 4.088 and a variance of 22.712%. The main variables in this factor include adequate computer laboratories, department libraries, expert and competent teachers, and technology integration in learning, which emphasize the importance of facility quality in attracting students' interest. The promotion factor, with an eigenvalue of 1.743 and a variance of 9.685%, includes creative and informative promotions and information through mass media and advertising, which play a role in increasing prospective students' awareness of the study program. The location and social factor, with an eigenvalue of 2.431 and a variance of 13.507%, highlights the importance of comfortable buildings and strategic campus locations in influencing students' choices. The job prospect factor has an eigenvalue of 1.351 with a variance of 7.503%, indicating that good job opportunities and flexibility of graduates in various job sectors are the main considerations of students. Finally, the comfort factor, with an eigenvalue of 1.148 and a variance of 6.378%, includes a safe environment without the threat of crime that creates a conducive learning atmosphere. These five factors provide important insights for designing more effective educational and promotional strategies in increasing the attractiveness of mathematics majors.

The contribution of numerical analysis to the results of this factor analysis can be seen through two main aspects, namely eigenvalues and percentage variance. Eigenvalues indicate how much each factor contributes to explaining the total variation of the data. The Facility Privileges factor has the highest eigenvalue of 4,088, indicating its most significant contribution to the data variance, followed by the Location and Social factors with an eigenvalue of 2,431, Promotion 1,743, Job Prospects 1,351, and Convenience 1,148. Meanwhile, the percentage variance, which indicates the contribution of each factor to the total variance explained by all factors, shows that the Facility Privileges factor contributes 22,712%, followed by Location and Social with a contribution of 13,507%, Promotion 9,685%, Job Prospects 7,503%, and Convenience 6,378%. Overall, this analysis shows that the Facility Features factor has the largest contribution in influencing student preferences, while Convenience has the smallest contribution. This provides important insights for the development of more effective educational and promotional strategies to increase the attractiveness of mathematics majors.

To strengthen the validation of the PCA results and improve understanding of the contribution of each factor, additional numerical analysis was performed using Monte Carlo simulations. This simulation aims to test the sensitivity of the PCA results to small changes in the input data. A total of 1,000 iterations were performed by adding random Gaussian noise to the original data, with a standard deviation of 5% of the mean value of each variable. The results of the numerical analysis using Monte Carlo simulation can be seen in the following table:

Table 10. Monte Carlo Simulation Results for Eigenvalue Stability and Variance Contribution

Factor	Average Eigenalue	Eigenvalue Standard Deviation	Average Variance (%)	Standard Deviation Variance (%)
Privileges and Facilities	4.072	± 0.039	22.7	± 0.2
Lecture Building and Social	2.418	± 0.025	13.5	± 0.1
Promotion	1.728	± 0.032	9.7	± 0.1
Job Prospects	1.345	± 0.020	7.5	± 0.1
Comfort	1.140	± 0.018	6.4	± 0.1

Table 10 shows the stability of eigenvalue and variance contribution of each factor obtained through Monte Carlo simulation of 1,000 iterations. The first factor, Privileges and Facilities, has the highest average eigenvalue of 4,072 with a contribution to variance of 22.7% (±0.2%), indicating that this factor has the most significant influence in explaining data variability. The second factor, Lecture Building and Social, has an average eigenvalue of 2,418 with a variance contribution of 13.5% (±0.1%). The third factor, Promotion, has an average eigenvalue of 1,728 with a variance contribution of 9.7% (±0.1%). The fourth factor, Job Prospects, showed an average eigenvalue of 1,345 and a variance contribution of 7.5% (±0.1%), while the fifth factor, Comfort, had an average eigenvalue of 1,140 with a variance contribution of 6.4% (±0.1%). These results confirm that the factor structure is stable, with consistent variance contributions even when the data undergoes small changes.

Table 11. Stability of Variable Loadings on Factors

Factor	Main Variables	Average Loading	Loading Standard Deviation
Privileges and Facilities	X11: Adequate Computer Lab	0.754	± 0.015
	X12: Department Library	0.772	± 0.018
	X13: Expert and Competent Teachers	0.536	± 0.012
	X15: Applied Mathematics	0.690	± 0.020
	X16: Integration with Technology	0.732	± 0.017
Lecture Building and Social	X7: Comfortable Lecture Building	0.739	± 0.014
	X8: Strategic Location	0.628	± 0.012
	X21: Parent Background	0.561	± 0.010
	X23: Affordable Fees	0.671	± 0.013
Promotion	X2: Creative Promotion	0.754	± 0.018
	X1: Mass Media Advertisement	0.689	± 0.016
Job Prospects	X17: Good Job Opportunities	0.724	± 0.012
	X18: Flexibility in Job Placement	0.868	± 0.014
Comfort	X10: Safe and Peaceful Environment	0.781	± 0.016
	X24: Low Crime Rate	0.574	± 0.012

Table 11 shows the stability of the loading of the main variables on each factor. The first factor, Privileges and Facilities, consists of variables such as Adequate Computer Lab (X11) with an average loading of 0.754 (±0.015) and Integration with Technology (X16) with an average loading of 0.732 (±0.017), indicating a strong relationship between these variables and the factor. The second factor, Lecture Building and Social, is supported by variables such as Comfortable Lecture Building (X7) with an average loading of 0.739 (±0.014) and Affordable Fees (X23) with an average loading of 0.671 (±0.013). The third factor, Promotion, has main variables such as Creative Promotion (X2) with an average loading of 0.754 (±0.018) and Mass Media Advertisement (X1) with an average loading of 0.689 (±0.016). The fourth factor, Job Prospects, consists of variables such as Good Job Opportunities (X17) with an average loading of 0.724 (±0.012) and Flexibility in Job Placement (X18) with the highest loading of 0.868 (±0.014). The fifth factor, Comfort, has variables such as Safe and Peaceful Environment (X10) with an average loading of 0.781 (±0.016). This analysis shows that the relationship between variables and factors remains stable, confirming the validity of the model.

Numerical analysis enhances the robustness and reliability of factor analysis in educational research. For institutions, these findings highlight the importance of facilities, promotions, and job prospects in attracting students to mathematics majors. By leveraging numerical methods, universities can design data-driven strategies to improve enrollment.

Locally, the research helps institutions in Indonesia and Nigeria understand the unique needs of their students, enabling data-driven policymaking to increase enrollment in mathematics majors. Globally, the research provides insights into strategies that can be implemented across countries to increase interest in mathematics education, which is essential in the era of digital transformation and data-driven learning.

This research has significant implications for the development of educational strategies at both local and global levels. Locally, the results provide insights for educational institutions in Indonesia and Nigeria to increase the attractiveness of mathematics majors through improved facilities, more effective promotional strategies, and the development of curricula that are relevant to the needs of the job market. Globally, these findings can be adapted by institutions in various countries to address similar challenges, especially in promoting mathematics education in the data-driven era. By understanding student preferences, universities can take proactive steps to address the needs of prospective students while strengthening their competitiveness in the international arena.

However, this study has several limitations. First, the sample used is limited to two universities, so the generalization of the results may not fully reflect the preferences of students in other regions. Second, this study only uses quantitative methods, without in-depth exploration through qualitative methods such as in-depth interviews or focus group discussions, which can provide a more comprehensive understanding. Third, external factors such as education policies and local economic conditions are not analyzed specifically, even though they can affect student preferences. Therefore, further research is recommended to expand the geographical scope, integrate qualitative methods, and include analysis of the influence of external factors.

4. CONCLUSION

Factors that influence students in choosing the Mathematics Department of the Faculty of Science and Technology at a University in Sumatera Island, Indonesia, as well as students of the Mathematics Department of the Faculty of Science at a University in Lagos City, Nigeria consist of 19 variables grouped into 5 factors, namely: the first factor is privileges and facilities with an eigenvalue of 4.088%, the second factor is the Lecture Building and Social factor with an eigenvalue of 2.431%, the third factor is the promotion factor with an eigenvalue of 1.743%, the fourth factor is the job factor with an eigenvalue of 1.351%, the fifth factor is the comfort factor with an eigenvalue of 1.148%. To expand on the findings of this study, recommendations for further research involve universities from more diverse regions, including countries with different levels of mathematics education participation, to obtain more globally representative results.

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