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Research Article

The Logistics Factors that Affect the Academic Achievement of Elementary School Students in the Kingdom of Saudi Arabia (Applied Statistical Study)

S. A. Alsawadi*, Salwa L. AlKhayyat, R. A. Bakoban
University of Jeddah, College of Science, Department of Mathematics and Statistics, Jeddah, Saudi Arabia

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ABSTRACT

This study aimed to examine the impact of logistical services on the academic achievement of primary school students using Exploratory Factor Analysis (EFA) and Stepwise Discriminant Analysis (DA). The EFA revealed five factors that explained 64.1% of the total variance: School Environment, Distance Between School and Home, Logistics Factors 1, Level of Education According to School Location, and Logistics Factors 2. These factors were extracted based on eigenvalues greater than 1 and were rotated using the Varimax method. Subsequently, four of these components were sequentially entered into the discriminant model through stepwise analysis: Level of Education According to School Location, Logistics Factors 1, Logistics Factors 2, and School Environment. Results indicated that Level of Education by Location was the most significant discriminator (Wilks' Lambda = .338, F = 3420.828, p < .001), followed by logistical and environmental factors. The final model achieved a Wilks' Lambda of .203. The standardized canonical discriminant function coefficients showed that the Level of Education According to School Location had the most decisive influence on the first discriminant function (1.055). As results indicate:

- School location significantly impacts academic achievement, whether a school is located in an urban or rural area.
- Improving logistical services, such as school transportation and delivering the textbook early, as the delay of these factors affects student achievement negatively.
- Attention to the school environment, including lighting, ventilation, and recreational facilities, positively affects students' academic achievement.
- The study recommends conducting future studies to investigate the remaining variables using alternative statistical methods.

1. INTRODUCTION

Education is identified as a cornerstone of the development process. Also, it is a weapon to improve one's life. It is probably the most important tool to change one's life. Education for a child begins at home. It is a lifelong process that ends with death. Education determines the quality of an individual's life, improves knowledge and skills, and develops personality and attitude.

Education is the foremost and fundamental right of every child. Ensuring accessibility to all children is not only the duty of the government but also of parents. The main objective of primary education is to bring awareness among the children, open avenues of opportunities along with self-development, and reduce

* Corresponding author; E-mail: sumaya.alsawadi@gmail.com

intergenerational poverty. It is the first step in the making of welfare and society. Primary education is a prerequisite for continuous development. The role of primary education is to ensure the development of children. This means that all children can develop their social, cognitive, cultural, emotional, and physical skills according to the best of their abilities to get a quality primary education.

Due to the serious interest of the Kingdom of Saudi Arabia in education, one of the goals of the 2030 vision is to improve the outputs of the education and training system at all stages from early education to continuous education, and provide training to reach the international levels through education, rehabilitation, and training programs that keep abreast of modern times and requirements, and are in line with the needs of development and the local and global labor market in partnership with all relevant parties locally and internationally. Furthermore, the Kingdom Vision 2030 sets goals to achieve comprehensiveness, quality, flexibility, and serve all segments of society to promote the Kingdom's regional leadership and international competitiveness. Saudi Vision 2030 [1]. In addition, Studies conducted by the World Bank [2] and the OECD [3] highlight that overcrowding can hinder students' ability to concentrate and perform well, especially in underserved areas.

At the same time, multivariate statistical approaches have become increasingly valuable, enabling the reduction of data complexity and the uncovering of latent dimensions. Applying EFA and DA offers insights into the structural relationships among variables and helps identify predictors. This study uses factor and discriminant analysis to define the logistics factors affecting elementary students' academic achievement.

2. LITERATURE REVIEW

This section offers a review of previous research that informs the present study in two main areas: (1) Studies that examined logistical factors and (2) research that used statistical methods—specifically exploratory factor analysis (EFA) and discriminant analysis (DA), to look at trends and the connections. This section establishes the conceptual and methodological foundation for the current research by reviewing contributions across these two domains.

2.1 The education and logistics studies

Usman [4] proposed a quality management model for the academic supply chain within higher education institutions in Indonesia. Adopting an exploratory case study approach, the research identified key factors that facilitate the successful implementation of supply chain quality management in academic operations. Data were collected through in-depth interviews and analyzed using open, axial, and selective coding in NVivo 11 Pro. The study concluded with a framework that integrates TQM principles with academic supply chain processes, offering valuable insights for educational institutions and service-based sectors with strong client–provider interactions.

Bonilla-Mejía and Londoño-Ortega [5] examined how geographic isolation—measured as travel distance and time to the nearest education services—affects learning in rural Colombian schools. Using spatial regression discontinuity analysis, the study found that each additional hour of travel time to the nearest administrative center reduced student test scores by approximately 0.34 standard deviations. The authors highlight that greater distance is associated with less frequent teacher presence and lower resource availability, ultimately impairs educational outcomes.

2.2 The statistical methods studies

Alrowaithy et al. [6] applied exploratory factor analysis to identify the primary drivers behind domestic violence against women in the Saudi context. The study revealed six underlying factors—work conditions, family dynamics, frequency of abuse, characteristics of the abuser, income level, and environmental context—which together accounted for approximately 60% of the total variance. Factor analysis reduced variable complexity and enhanced the interpretability of interrelated causes.

Qanawi and Ali [7] explored the factors influencing academic achievement among secondary school students in the Kenana Sugar Company schools. Using exploratory factor analysis, the study extracted seventeen factors that explained 65.5% of the total variance. The influential factors were the economic factor (28.8%) and the social factor (19.3%). In contrast, school age emerged as the least influential variable, accounting for just 2.14% of the explained variance. These findings show that factor analysis helps identify key determinants.

2.3 Theoretical Foundations of Logistical Factors

Theoretical frameworks help explain how logistical variables affect educational results while supporting existing empirical research findings. According to Maslow's hierarchy of needs [8], people need to satisfy their basic physiological requirements and safety needs before they can advance to higher cognitive functions. The basic needs of students need to be satisfied before they can effectively participate in learning activities.

Bronfenbrenner's ecological systems theory [9] demonstrates how child development results from environmental systems, which include both immediate settings such as family and school (microsystem) and broader contextual influences (exosystem). The perspective shows that academic achievement can be affected by structural or contextual barriers that exist in a student's environment. These theories establish a conceptual framework to incorporate logistical aspects when studying educational results.

3. MATERIALS AND METHODS

In this study, the data were collected through a questionnaire distributed to all available means. It was developed using Demographic questions and a 3-point Likert scale. We used factor and discriminant analyses to analyze the data and determine the logistics factors affecting academic achievement by using SPSS version 25, one of the most popular applications in psychological research and social science. The data included 5239 families from different regions of the Kingdom of Saudi Arabia who had at least one child in primary school from September 2020 to September 2023. The data included the following variables: school location, distance between school and home, delay in receiving school books, The school cafeteria provides basic needs, transportation used to go to school, and time spent arriving at school, school private transportation, the number of students in the class, adequate lighting, good ventilation, adequate spaces, and playgrounds, school cleanliness, and the student results in the last semester.

Exploratory Factor Analysis (EFA) is a multivariate statistical technique used to uncover the underlying structure of a set of observed variables. It aims to reduce data dimensionality by revealing latent constructs (factors) that account for the correlations among the observed indicators. Hair et al. [10]

Mathematically, the EFA model assumes that each observed variable can be expressed as a linear combination of a smaller number of common factors, as shown below:

$$F_i = b_{i1}X_1 + b_{i2}X_2 + \cdots + b_{ij}X_j \qquad (3.1)$$

Where:
i: Factor, $i = 1, 2, \dots, m$
b_i: Factor coefficients
X: The independent variable
j: Number of variables, $j = 1, 2, \dots, p$
m: The total number of extracted factors
p: The total number of observed variables

The primary goal is to estimate the factor loadings X, representing the strength and direction of the relationships between variables and factors. High loadings suggest that the variable is strongly associated with the factor.

In typical applications, it is assumed that the factors are uncorrelated (in orthogonal rotations), and that the unique errors are uncorrelated with each other and the common factors. The following section presents the application of EFA to the study dataset.

3.1.1 Assumptions of factor analysis:

1. Sample Size, Hair et al. [10] suggested that sample sizes should be at least 100. Tabachnick and Fidell [11] suggested that at least 300 cases are required for factor analysis. Chua [12] suggested that the sample sizes should exceed five times the number of variables. This study involved 5239 respondents.
2 The Kaiser-Meyer-Olkin measure of sampling adequacy is a statistical value that is used as an index for deciding whether or not the sample is sufficient for performing factor analysis, Bartlett's test of sphericity is a second measure of sampling adequacy; it tests for the overall significance of all correlations among all items on the measuring instrument. The Kaiser-Meyer Olkin to measure sampling adequacy (KMO) (must be more than 0.50), Hair et al. [10]. This is supported by the requirement of KMO above the acceptable limit of 0.50. Thus, Bartlett's test of sphericity (significant at $p < 0.001$) was used to assess the suitability of the sample for principal component analysis.

Table 1. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.586
Bartlett's Test of Sphericity	Approx. Chi-Square	17621.766
	df	78
	Sig.	.000

Table 1 presents the results of KMO and Bartlett's Test where, Kaiser-Meyer Olkin measure of sampling adequacy (KMO), which was 0.586 (> 0.50), which is acceptable, and Bartlett's test of sphericity was significant ($p < 0.001$), meaning that the correlations between variables are significantly different from zero.

These two statistical values (the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity) provide standards that should be met before conducting a factor analysis.

3.1.2 The Result of Exploratory Factor Analysis

This study selected Principal Components Analysis (PCA) as the extraction method. This approach identifies the factors that explain the highest variance in the data. Hutcheson [14] has said the Kaiser rule is considered the easiest and most common method. The procedure is used to get all the components with eigenvalues larger than 1. Such a method estimates the optimal number of components to depict the data. Using PCA, every factor extracted is shown by an eigenvector. An eigenvector is defined as a weight column, each of which accompanies an element in the correlation matrix.

The eigenvalue for a given factor measures the variance in all the variables accounted for by that factor. The eigenvalues used for each factor extracted are usually greater for the first and least for the last factor extracted. Boslaugh [15]

Table 2. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.591	19.933	19.933	2.591	19.933	19.933	1.979	15.221	15.221
2	1.924	14.803	34.736	1.924	14.803	34.736	1.970	15.157	30.379
3	1.638	12.603	47.339	1.638	12.603	47.339	1.653	12.714	43.093
4	1.151	8.857	56.196	1.151	8.857	56.196	1.498	11.526	54.619
5	1.029	7.916	64.112	1.029	7.916	64.112	1.234	9.493	64.112
6	.979	7.533	71.645						
7	.903	6.949	78.594						
8	.787	6.054	84.649						
9	.600	4.614	89.263						
10	.518	3.988	93.250						
11	.439	3.379	96.630						
12	.322	2.475	99.105						
13	.116	.895	100.000						
Extraction Method: Principal Component Analysis.									

From Table 2, we notice that the Principal Component Analysis revealed five components with eigenvalues exceeding 1, collectively accounting for approximately 64.1% of the total variance.

Cattell [16] proposed the scree test, in which eigenvalues are plotted against component numbers in descending order. The test involves identifying the point at which the slope of the curve noticeably changes, forming an "elbow." The number of components above this break point represents the meaningful factors, while the eigenvalues below the break are assumed to reflect error variance or noise.

Figure 1. Scree plot

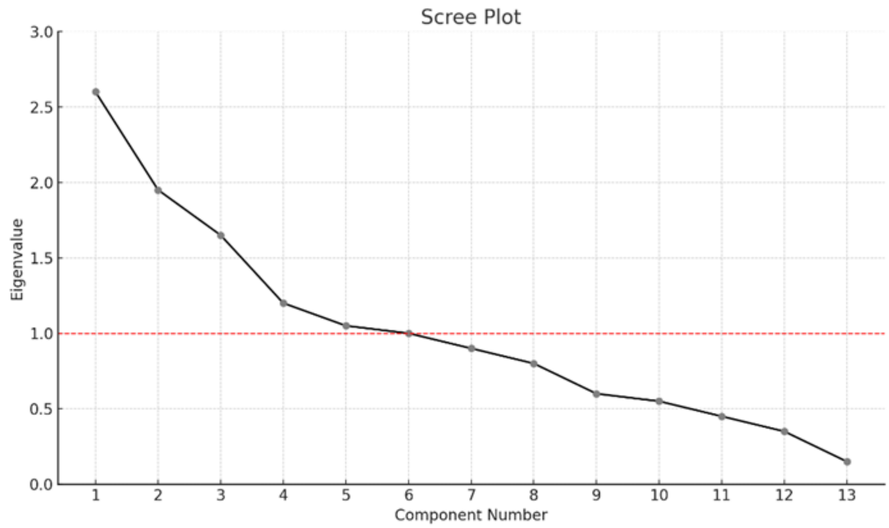

Figure 1 shows that five extracted factors appear above the point where the curve begins to flatten, indicating the elbow or break point. These components are associated with eigenvalues greater than 1, suggesting they explain a meaningful amount of variance in the dataset.

After factor analysis, rotation emerged and was developed to support researchers in showing the findings of a factor analysis. The rotation method has several options. Each option depends on several algorithms or ways to accomplish a similar broad aim—simplification of factor structure. There are two main classes of rotation methods: oblique and orthogonal. Osborne [17]

The Varimax rotation method was applied to enhance the interpretability of factors by maximizing the variance of squared loadings across variables. This method increases the clarity of the factor structure by making high loadings even higher and low loadings lower, ensuring that each variable is strongly associated with one factor. However, it may also distribute the variance of major factors across smaller factors, which can slightly reduce the clarity of the overall factor structure. Costello [18]

The rotated component matrix supported a five-factor solution, indicating a coherent multidimensional structure underlying the observed variables. The extracted components represent distinct yet interrelated domains. Below is a detailed analytical interpretation of each factor and its linear mathematical expression.

The first factor:

$$F_1 = 0.736\ (adequate\ lighting\ ) + 0.867(good\ ventilation) \\ + 0.604\ (adequate\ spaces\ and\ playgrounds)$$

This factor holds the highest explanatory value among the extracted components, as it accounts for 15.221% of the total variance after rotation. It consists of three variables that relate to the quality of school infrastructure. The strong positive loadings indicate a high degree of internal consistency, suggesting that well-ventilated, well-lit environments with sufficient playgrounds are central to shaping student perceptions. Therefore, it was labeled the "School Environment" factor.

The second factor:

$$F_2 = 0.948(\textit{distance between school and home}) + 0.946\ (\textit{time spent to arrive at school})$$

This factor explains 15.157% of the total variance and focuses on spatial accessibility. It includes two highly correlated variables that reflect physical proximity to school. The high loadings suggest a significant impact of commuting distance and duration on students' academic contexts. Accordingly, this factor is termed the "Distance from School" factor.

The third factor:

$$F_3 = 0.461\ (\text{delay in receiving school books}) + 0.699(\text{transportation used to go to school}) - 0.767(\textit{ school private transportation})$$

Accounting for 12.714% of the variance, this factor combines variables related to logistical support. The structure suggests contrasting experiences—general transportation and delivery delays on one hand, and private school transportation on the other. The negative coefficient for private transportation indicates an inverse relationship. This pattern justified naming it the "Logistics Factor 1."

The fourth factor:

$$F_4 = 0.746\ (\textit{school location}) + 0.797(\textit{result in the last semester})$$

With 11.526% of the variance explained, this factor merges academic achievement with the geographic setting of schools. The significant positive loadings imply that students in specific locations, such as a city or a village, may have consistently different performance levels. Thus, it is named the "Level of education according to school location" factor.

The fifth factor:

$$F_5 = 0.550\ (\textit{school cafeteria provides basic needs}) + 0.516\ (\textit{number of students in the class}) + 0.691(\textit{ School cleanliness})$$

This factor explains 9.493% of the variance and represents perceptions related to services and comfort within the school. Cleanliness, crowding, and food access shape students' everyday experience. These themes support labeling this component the "Logistics Factor 2."

3.2 Discriminant analysis

Discriminant analysis is a multivariate statistical technique used when the dependent variable is categorical and the independent variables are continuous or interval-scaled. It is employed to determine which variables discriminate between two or more naturally occurring groups. It aims to find a linear combination of variables (discriminant functions) that best separates the groups. Mathematically, the general form of the discriminant function is given by:

$$D = b_0 + b_1X_1 + b_2X_2 + \ldots + b_pX_p \qquad (3.2)$$

Where:

D: Discriminant score

b_0: Constant term

$b_1 ... b_p$: Discriminant coefficients
$X_1 ... X_p$: Predictor variables

Discriminant analysis is similar to multiple linear regression but with a categorical dependent variable. It assumes multivariate normality, homogeneity of variance-covariance matrices, and independence among observations. This method is beneficial in classifying cases into known groups and understanding the structure of group differences. Hair et al. [10].
This section presents the main concepts of discriminant analysis and its applications to the data resulting from Exploratory factor analysis. The factors extracted from the exploratory factor analysis were entered as independent variables, and the students' results were the dependent variable in the discriminant analysis. The students' results were operationalized using categorical self-reported academic performance levels (failed, good, very good, and excellent).

3.2.1 Assumptions of Discriminant Analysis

Discriminant Analysis requires some assumptions. The main assumptions of Discriminant analysis are tested. The SPSS program tests the normality, homogeneity, and difference of group means assumptions. That will show whether the data fits the Discriminant analysis or not.
Before conducting the discriminant analysis, a preliminary test of equality of group means was performed to determine whether the independent variables significantly differentiated between the groups. The Tests of Equality of Group Means resulted on, four out of the five variables demonstrated statistically significant differences among the groups ($p < .001$), with particularly strong discrimination observed for “Level of education according to school location” (Wilks’ Lambda = .338, $F(3, 5235) = 3420.828$, $p < .001$). This confirms the appropriateness of including these variables in the discriminant model. According to Hair et al. [10], variables with significant F-values in this test are considered promising candidates for discriminant function construction.
Table 3 presents the Box’s M test which was conducted to test the assumption of homogeneity of variance-covariance matrices across the groups. The test yielded a statistically significant result (Box’s M = 3181.821, F = 102.208, df1 = 30, df2 ≈ 9559, $p < .001$). as noted by Tabachnick and Fidell [11], discriminant analysis is generally robust to moderate violations of this assumption, particularly when group sizes are relatively large and balanced, as is the case in the present study.

Table3.Box's M

Box's M		3181.821
F	Approx.	102.208
	df1	30
	df2	9558.777
	Sig.	.000
Tests null hypothesis of equal population covariance matrices.		

3.2.2 The Result of Discriminant Analysis by Stepwise Method

Table 4 shows the result of variables entered/removed in the stepwise discriminant analysis. It provides a detailed view of how variables were sequentially included in the model based on their discriminatory power.

Table 4. Variables Entered/Removed

Step	Entered	Wilks' Lambda											
		Statistic	df1	df2	df3	Exact F				Approximate F			
						Statistic	df1	df2	Sig.	Statistic	df1	df2	Sig.
1	Level of education according to school location	.338	1	3	5235.0	3420.8	3	5235.0	.00				
2	Logistics factors 1	.250	2	3	5235.0	1741.7	6	10468.0	.00				
3	Logistics factors 2	.219	3	3	5235.0					1228.2	9	12735.9	.00
4	school environment	.203	4	3	5235.0					952.4	12	13842.9	.00

At each step, the variable that minimizes the overall Wilks' Lambda is entered.
a. Maximum number of steps is 10, b. Minimum partial F to enter is 3.84.
c. Maximum partial F to remove is 2.71, d. F level, tolerance, or VIN insufficient for further computation.

The results shows that the first variable entered was Level of education according to school location, followed by Logistics factors 1, Logistics factors 2, and School environment. Each step resulted in a significant improvement in the model's discriminatory power, indicating a strong separation between groups.

Following the stepwise entry of variables, the standardized canonical discriminant function coefficients were examined to assess the relative contribution of each predictor to the three discriminant functions. According to Hair et al. [10], the standardized canonical discriminant function coefficients indicate the relative contribution of each predictor to group separation. Larger absolute values suggest a stronger ability to discriminate between the groups. These coefficients assist in interpreting the structure of the discriminant function and understanding which variables drive group differentiation. Although the second Factor Distance from School" showed statistical significance in EFA, it was excluded from the Discriminant Analysis due to its limited discriminatory power across the defined achievement groups. Its contribution was not substantial in distinguishing between categories of the dependent variable.

Table 5. Standardized Canonical Discriminant Function Coefficients (SDC)

Factors	Function		
	1	2	3
school environment	.109	.510	.784
Logistics factors 1	-.531	.721	-.491
Level of education according to school location	1.055	.188	-.116
Logistics factors 2	.316	-.520	-.133

Table 5 shows that, the first function was mainly defined by the level of education by location (1.055), making it the strongest factor in group discrimination. Logistics Factors 1 had a negative contribution (–0.531), indicating an inverse relationship. The second function was shaped by Logistics Factors 1 (0.721) and school environment (0.510), highlighting a combination of logistical and environmental influences. In contrast, Logistics Factors 2 negatively impacted this function (–0.520). The third function was most influenced by the school environment (0.784), suggesting that infrastructure-related factors played a key role in this dimension.

Discriminant Function Equations:

$$\mathrm{SDC}_1 = 0.109(School\ Environment) - 0.531(Logistics\ 1) + 1.055(Education\ by\ Location) + 0.316(Logistics\ 2)$$

$$\mathrm{SDC}_2 = 0.510(School\ Environment) + 0.721(Logistics\ 1) + 0.188(Education\ by\ Location) - 0.520(Logistics\ 2)$$

$$\mathrm{SDC}^3 = 0.784(School\ Environment) - 0.491(Logistics\ 1) - 0.116(Education\ by\ Location) - 0.133(Logistics\ 2)$$

Figure 2. Canonical discriminant functions

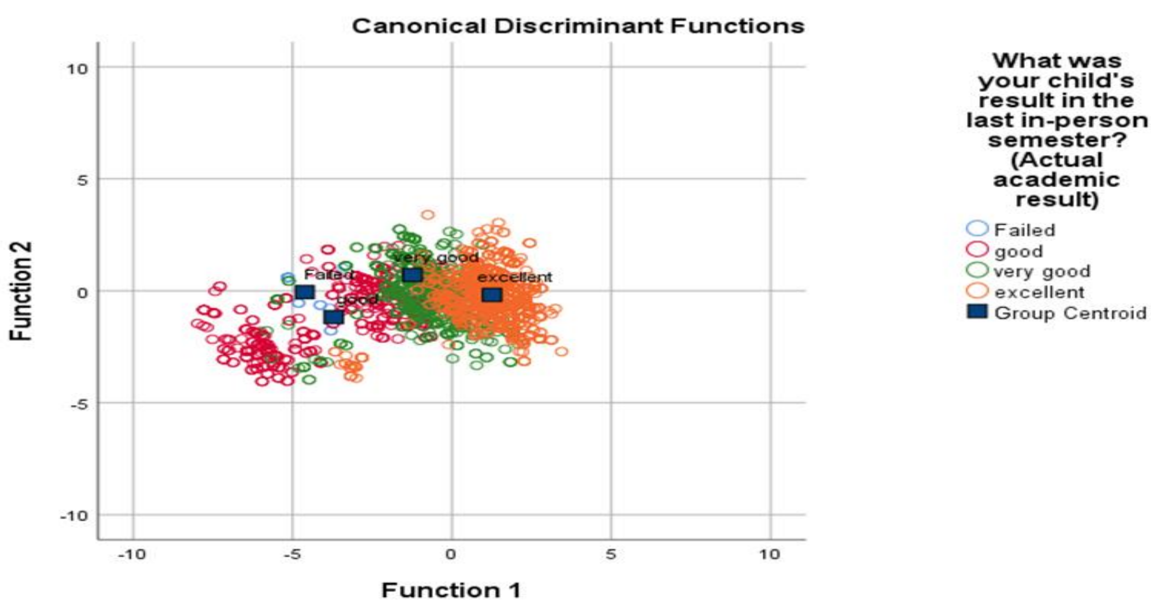

Figure 2 illustrates the distribution of cases across the first two canonical discriminant functions based on students' results (failed, good, very good, and excellent). Each colored circle represents an individual case, while the squares indicate the group centroids—i.e., the average location of each group in the discriminant space.

The plot reveals a clear separation between categories, especially along Function 1. Students classified as “failed” are concentrated on the far left of the Function 1 axis, while “excellent” students are primarily distributed toward the right. This indicates that Function 1 is the most influential dimension in distinguishing between performance levels, capturing most of the group variance.

Function 2 contributes less to the separation but helps distinguish between intermediate categories, particularly “Good” and “Very Good,” which show some vertical spread. The plot shows that the model effectively tells apart different student performance groups and backs up the statistical findings from the stepwise discriminant analysis.

4. Conclusion and Recommendation

This study examined the effect of logistical factors on the academic achievement of primary school students using exploratory factor analysis (EFA) and stepwise discriminant analysis (DA).

The EFA revealed five key components that explained 64.1% of the total variance: School Environment, Distance Between School and Home, Logistics Factors 1, Level of Education According to School Location, and Logistics Factors 2. These components were extracted based on eigenvalues greater than 1 and rotated using the Varimax method to improve interpretability.

After applying the factors to discriminant analysis, the test showed that four factors were sequentially entered into the model in the stepwise discriminant analysis. The factors are (Level of Education, Logistics Factors 1, Logistics Factors 2, School Environment).

The discriminant analysis showed that Level of Education According to School Location was the first and most significant discriminator (Wilks' Lambda = .338, F = 3420.828, $p < .001$), followed by Logistics Factors 1, Logistics Factors 2, and School Environment. The final model achieved a Wilks' Lambda of .203, indicating strong discriminatory power.

The standardized canonical discriminant function coefficients confirmed that Level of Education According to School Location had the strongest influence on the first discriminant function (1.055), while various combinations of the remaining variables shaped other functions.

The canonical plot showed clear group separation along the first two discriminant functions, particularly between the "Failed" and "Excellent" performance categories, reinforcing the model's statistical validity.

Based on the above, we recommend paying attention to:

1. School location: If the school is in a city or village. The results indicated that school location clearly impacts students' academic achievement.
2. Logistical factors, such as transportation and delayed textbook delivery. The results indicated that the delay of these factors negatively contributes to academic achievement. This requires improving the efficiency of support services and facilitating regular and timely access to educational resources.
3. The school environment, including good lighting, ventilation, and the availability of playgrounds, is one of the factors that positively influences group discrimination. This means that enhancing the quality of the school environment contributes to raising students' academic achievement.
4. Reconduct the study more extensively to examine the remaining factors using different statistical methods.

Author Contribution

- Conceptualization, Data curation: S.A. Alsawadi
- Formal analysis, Validation: S. L AlKhayyat
- Writing - original draft:, Writing - review editing: R.A. Bakoban

Conflicts of Interest

The author declares no conflicts of interest.

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Data Availability Statement

The generated datasets used and evaluated in this research study are provided in the form of graphs and tables within the manuscript.

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