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Comparative analysis of varimax and Promax rotation methods in exploratory factor analysis

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Abstract: This study compares two widely used rotation techniques in exploratory factor analysis (EFA): Varimax, an orthogonal method, and Promax, an oblique method. Sample data from 394 students were analyzed using JASP software to evaluate the two methods. Both rotations identified latent constructs influencing academic achievement after factor extraction via principal axis factoring. Although both methods retained the same number of factors, the pattern and magnitude of variable loadings differed. The Kaiser-Meyer-Olkin (KMO) test indicated superior reliability for Promax, which achieved significantly higher sampling adequacy (MSA = 0.882) compared to Varimax (MSA = 0.500). Bartlett's test confirmed the suitability of factor analysis by revealing significant interrelationships among variables ($p < 0.001$). Promax results were easier to interpret, revealing moderately positive inter-factor correlations and explaining 59% of the cumulative variance, compared to 56% for Varimax. Conversely, Varimax produced uncorrelated factors, ideal when factor independence is desired. Parallel analysis supported the retention of three factors for both methods. Path diagrams further illustrated Promax's performance in capturing related constructs. Overall, the findings suggest that Promax outperforms Varimax in handling interrelated constructs, offering higher reliability and accounting for a greater proportion of variance. In contrast, Varimax, based on the assumption of factor independence, provides a clearer but less nuanced interpretation.

Keywords: *Exploratory factor analysis, Factor rotation, JASP, Promax, Varimax.*

1. Introduction

Exploratory Factor Analysis (EFA) is a widely applied statistical technique across fields such as psychology, sociology, and education, used to uncover latent constructs underlying observed relationships among variables. A crucial component of EFA is the application of factor rotation techniques, which simplify the structure of factor loadings and enhance their interpretability. Two commonly utilized rotation methods are Varimax and Promax, each offering distinct advantages based on the characteristics of the data and the objectives of the research. Varimax, introduced by Kaiser [1] is an orthogonal rotation method that assumes factors are independent and maximizes the variance of squared loadings, making it particularly valuable for studies where uncorrelated factors are expected [2]. In contrast, Promax, an oblique rotation method, accommodates correlated factors, providing a more realistic representation of data structures where constructs naturally interact [3] Varimax is often lauded for its computational efficiency and ability to yield clear, interpretable solutions [4]. Its applicability in diverse domains such as public health and social sciences demonstrates its versatility for analyzing complex datasets [2]. Promax, on the other hand, is recognized for capturing real-world interrelationships among variables, making it particularly suitable for social science research [5]. Choosing the appropriate rotation method is critical, as an unsuitable selection can lead to misinterpretation of results and compromise research validity. Recent advancements in EFA

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methodologies have refined these techniques, highlighting their respective strengths and limitations [6]. A thorough understanding of the theoretical and practical implications of Varimax and Promax is essential for researchers aiming to derive meaningful insights while aligning their analytical approaches with the goals of their study. This study offers a comprehensive comparative analysis of Varimax and Promax rotation techniques within the framework of EFA. It evaluates their performance based on clarity of factor loadings, interpretability, and alignment with theoretical assumptions. By applying these methods to a dataset in academic achievement, the study explores how each technique identifies latent constructs, particularly in datasets with varying levels of inter-factor correlations. Building on recent methodological advancements, the study provides empirical evidence to guide best practices for selecting rotation methods in EFA [7, 8]. It emphasizes the contexts where Varimax excels in simplicity and Promax demonstrates flexibility, offering actionable insights for researchers. Ultimately, this work contributes to enhancing methodological rigor in factor analysis, equipping researchers with practical recommendations to ensure clarity and interpretability in their findings.

2. Literature Review

Factor analysis is a prevalent statistical method for determining latent variables underlying task performance or questionnaire responses. Factor analysis's main goal is to use fewer underlying latent factors to explain the variance seen in a big collection of variables or indicators [5]. Factor rotations may be broadly divided into two categories: (1) oblique rotations, in which factors are allowed to correlate, and (2) orthogonal rotations, in which factors are restricted to stay uncorrelated. There are several rotation techniques to maximize the factor structure within each category [9]. According to Costello and Osborne [10] the output of oblique rotation is just slightly more complicated than that of orthogonal rotation. Choosing the right rotation method in Exploratory Factor Analysis (EFA) is essential for achieving results that are both meaningful and interpretable. Varimax and Promax are among the most commonly employed techniques, each offering unique benefits depending on the structure of the dataset and the goals of the research. Varimax, which is an orthogonal rotation method, aims to maximize the variance of squared loadings, thereby ensuring that factors remain independent. This characteristic makes it particularly suitable for studies that require a clear and distinct separation of constructs [11]. On the other hand, Promax is an oblique rotation method that permits correlations between factors, making it especially advantageous for analyses where interrelationships among constructs are anticipated [7, 12]. Numerous studies have underscored the advantages of these methods. For instance, O'Brien [13] found Varimax to be particularly beneficial during the initial phases of questionnaire development, where clarity is paramount. Additionally, Alzayani, et al. [14] illustrated its effectiveness in enhancing construct validity within medical education by distinguishing various dimensions in student feedback. Conversely, in more intricate datasets, Promax frequently demonstrates greater efficacy. Research by Castro, et al. [4] ated that Promax yields more profound insights into dietary patterns, while [8] highlighted its capacity to uncover significant correlations in geochemical research. The selection of Varimax or Promax is based on the goals of the study. Varimax is ideal for datasets that highlight independent factors, whereas Promax is more appropriate for examining complex, interrelated connections. Matching the rotation technique with the study's theoretical framework guarantees strong, dependable outcomes and improves the clarity of factor analysis results. Varimax is the most commonly utilized rotation method in statistical analysis. As a method of orthogonal rotation, its main goal is to enhance the understanding of factors by reducing the number of variables that show high loadings on each factor. In particular, Varimax aims to maximize the variance of factor loadings by amplifying high loadings and reducing low loadings, thus improving the clarity and separateness of the factor structure [15]. Once the designated number of factors is extracted, a rotation is usually performed to reach a more understandable solution. Promax is acknowledged as a quick and effective technique for oblique factor rotation. In this process, a

preliminary Varimax rotation, typically followed by Kaiser normalization, is executed to achieve an orthogonal solution, which is later converted into an oblique solution. In this context, a short summary of the differences noted among different Promax implementations is offered [5].
Summary of the Varimax rotation method based on its mathematical formulation:

$$f(\Lambda) = [p \sum_{i=1}^{p} (\lambda_{ij}^2)^2 - \left(\sum_{i=1}^{p} (\lambda_{ij}^2)^2\right)^2]/p^2 \quad (1)$$

In the case of Promax rotation, the procedure involves raising the loadings obtained from the Varimax rotation to a specified power and then rotating the resulting matrix while allowing the factors to correlate [9].

3. Methodology and Materials

This study presents a comparative analysis of Varimax and Promax rotation techniques within the framework of Exploratory Factor Analysis (EFA), evaluating their effectiveness in enhancing factor interpretability. Data were collected through an electronic questionnaire administered to 394 students from a government university in the Kingdom of Saudi Arabia. The questionnaire assessed four dimensions influencing academic achievement: academic, socio-economic, personal, and environmental factors.

The dataset was screened for completeness, and missing responses were addressed using appropriate imputation techniques. EFA was then applied to identify latent constructs underlying the observed variables. Principal Axis Factoring (PAF) was chosen as the extraction method due to its robustness in handling non-normal data distributions. Parallel analysis was employed to determine the optimal number of factors to retain [10]. The study applied two rotation techniques: Varimax and Promax. Varimax, an orthogonal rotation method, maximizes the variance of squared loadings to ensure uncorrelated factors. Its objective function is expressed as Kaiser [1]:

$$Q = \sum_{j=1}^{m} \left[\frac{\sum_{i=1}^{n} (a_{ij}^2)^2}{\sum_{i=1}^{n} a_{ij}^2} \right] \quad (2)$$

Where:
Q: represents the total variance.
a_{ij}: denotes the factor loadings.
N: is the number of variables.
M: is the number of factors. Conversely.
Promax, an oblique rotation method, allows factors to correlate. The Promax algorithm modifies the loadings matrix L using a power parameter k to relax orthogonality, represented as Hendrickson and White [16]:

$$L^* = (L^{(k)})R^{-1} \quad (3)$$

Where:
L: is the transformed loadings matrix.
R: is the factor correlation matrix.
K: is a user-defined parameter.

The effectiveness of these rotation methods was assessed based on several criteria, including the simplicity of the factor structure, inter-factor correlations (specific to Promax), total variance explained, and the stability of factor solutions. JASP software was utilized for statistical analyses due to its advanced capabilities in performing EFA and implementing rotation techniques.

This methodology provides a structured approach for comparing Varimax and Promax in clarifying factor loadings and aligning with theoretical assumptions. The findings offer empirical guidance for researchers in selecting the most appropriate rotation method based on dataset characteristics and research objectives, enhancing the validity and interpretability of EFA results.

4. Results

The JASP software JASP Team [17] was utilized to analyze the data and compare oblique (Promax) and orthogonal (Varimax) rotation methods. Data were collected using a questionnaire (see Appendix 1).

Table 1.
Kaiser-Meyer-Olkin Test.

	Promax	Varimax
	MSA	**MSA**
Overall MSA	0.882	0.500
Q1	0.956	0.500
Q2	0.900	0.500
Q3	0.886	0.500
Q4	0.940	0.500
Q5	0.890	0.500
Q6	0.962	0.500
Q7	0.808	0.500
Q8	0.808	0.500
Q9	0.877	0.500
Q10	0.886	0.500
Q11	0.822	0.500
Q12	0.963	0.500
Q13	0.861	0.500
Q14	0.822	0.500
Q15	0.947	0.500
Q16	0.861	0.500
Q17	0.970	0.500
Q18	0.898	0.500

The table presents the results of the Kaiser-Meyer-Olkin (KMO) measure for assessing sample adequacy. In the Promax rotation, the overall Measure of Sampling Adequacy (MSA) is 0.882, which exceeds the threshold of 0.5, indicating strong sampling adequacy. In the Varimax rotation, the overall MSA is 0.500, meeting the minimum acceptable threshold of 0.5. These results suggest that both methods yield adequate sample sizes for factor analysis; however, the higher MSA value in Promax implies greater reliability in the extracted factors compared to Varimax.

Table 2.
Bartlett's Test.

Promax			**Varimax**		
X^2	df	p	X^2	df	p
15472.009	153.000	< .001	∞	153.000	< .001

From the table above, Bartlett's test yields a p-value of less than 0.01 for both the Promax and Varimax rotations, indicating that significant correlations exist among the variables and that the correlation matrix is not an identity matrix. Therefore, factor analysis is appropriate for these data. Additionally, the results obtained from both Promax and Varimax methods are identical.

Table 3.
Chi-squared Test.

	Promax			Varimax		
	Value	**df**	**p**	**Value**	**df**	**p**
Model	2533.355	102	< .001	42617.065	102	< .001

Both rotation methods yielded statistically significant results ($p < 0.001$); however, the larger chi-squared value observed for Varimax indicates differences in model fit between the two approaches.

Table 4.
Factor Loadings by using Promax.

	Factor 1	Factor 2	Factor 3	Uniqueness
Q16	1.010			0.120
Q13	1.010			0.120
Q15	0.791			0.294
Q5	0.718			0.506
Q17	0.694			0.590
Q2	0.666			0.525
Q4	0.665			0.463
Q18	0.650			0.573
Q1	0.504			0.614
Q9	0.427			0.705
Q14		1.102		0.015
Q11		1.102		0.015
Q12		0.490		0.571
Q7			1.106	0.013
Q8			1.106	0.013
Q6			0.420	0.725
Q3				0.890
Q10				0.653

Note: Applied rotation method is Promax.

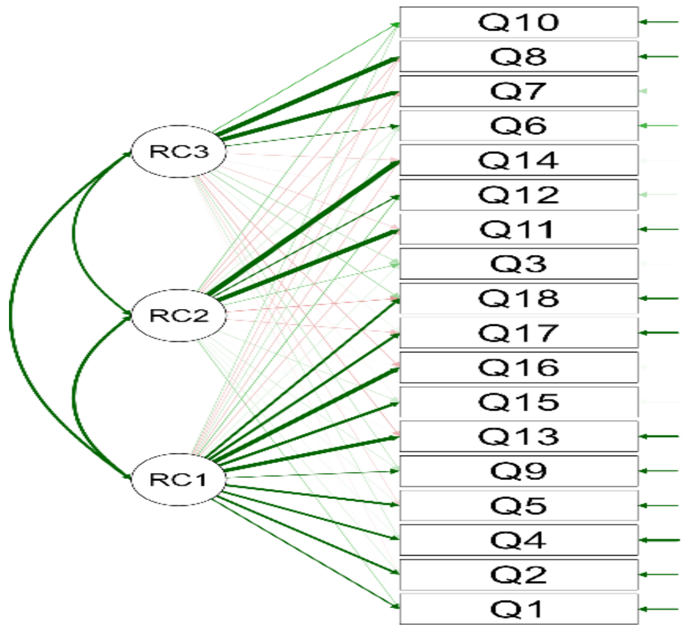

Figure 1.
Saturation chart of variables on factors using Promax.

From the table and figure above, three factors were extracted in each case, and each factor was saturated by several variables, with the degree of saturation decreasing progressively from Factor 1 to Factor 3. For Promax: - Factor 1 was saturated by ten variables (Q16, Q13, Q15, Q5, Q17, Q2, Q4, Q18, Q1, Q9). - Factor 2 was saturated by three variables (Q14, Q11, Q12). - Factor 3 was saturated by three variables (Q7, Q8, Q6). Correlations among these three factors were observed, as indicated by the lines representing relationships between them. This is a key feature of the Promax method, which assumes the presence of correlations between the extracted factors. Regarding column uniqueness, this represents the proportion of variance unexplained by the factors. A smaller uniqueness value indicates better explanation of the variance by the factors. While both methods identified three factors, the number of saturated variables in the Promax method was greater than in the Varimax method. The variables in each Promax factor are similar to those in the Varimax method, with one additional variable in each factor for the Promax rotation.

Table 5.
Factor loadings by using Varimax.

	Factor 1	Factor 2	Factor 3	Uniqueness
Q13	0.864			0.189
Q16	0.864			0.189
Q15	0.677			0.447
Q4	0.571			0.590
Q5	0.558			0.629
Q2	0.555			0.629
Q1	0.519			0.635
Q17	0.478			0.734
Q18	0.463			0.723
Q7		0.961		0.012
Q8		0.961		0.012
Q11			0.950	0.007
Q14			0.950	0.007
Q3				0.922
Q6				0.808
Q9				0.809
Q10				0.800
Q12				0.750

Note: Applied rotation method is Varimax.

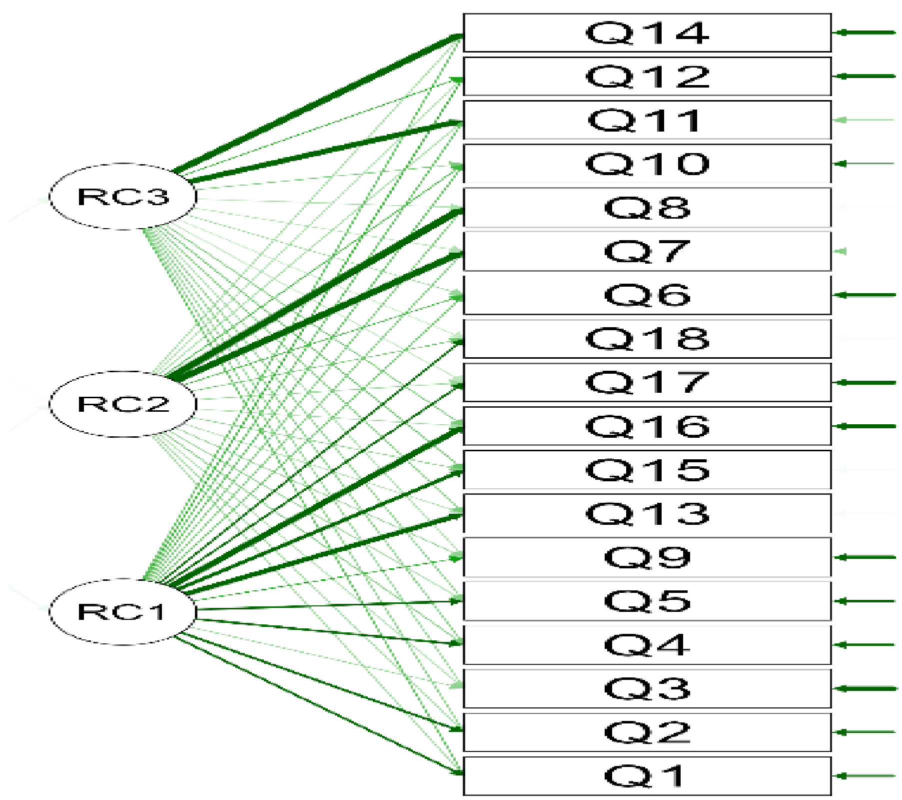

Figure 2.
Saturation chart of variables on factors using Varimax.

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From the table and figure above, three factors were extracted using the Varimax rotation method. The degree of saturation for each factor was ranked in descending order. Specifically, Factor 1 was saturated by nine variables (Q13, Q16, Q15, Q4, Q5, Q2, Q1, Q17, Q18); Factor 2 was saturated by two variables (Q7, Q8); and Factor 3 was saturated by two variables (Q11, Q14). In accordance with the Varimax method, which assumes that factors are uncorrelated, no correlations were observed among the three factors, as evidenced by the absence of connecting lines between them.

Table 6.
Factor loadings (Structure Matrix).

	Promax			**Varimax**		
	Factor 1	**Factor 2**	**Factor 3**	**Factor 1**	**Factor 2**	**Factor 3**
Q1	0.612			0.519		
Q2	0.688			0.555		
Q3						
Q4	0.730			0.571		
Q5	0.702			0.558		
Q6			0.516			
Q7			0.986		0.961	
Q8			0.986		0.961	
Q9	0.536					
Q10			0.553			
Q11		0.986				0.950
Q12		0.637				
Q13	0.934			0.864		
Q14		0.986				0.950
Q15	0.839			0.677		
Q16	0.934			0.864		
Q17	0.636			0.478		
Q18	0.639					

Note: Applied rotation method is Promax. Applied rotation method is Varimax.

The table above presents the factor loadings for each variable following the rotation process. It displays the saturation levels of each variable with the extracted factors. In the case of the Promax rotation, a variable can exhibit significant loadings on multiple factors simultaneously, reflecting the assumption that the factors are correlated. In contrast, the Varimax rotation method typically assigns each variable to a single factor, in line with the assumption that the factors are uncorrelated.

Table 7.
Factor Characteristics by using Promax.

Factor Characteristics							
		Unrotated solution			**Rotated solution**		
	Eigenvalues	**SumSq. Loadings**	**Proportion var.**	**Cumulative**	**SumSq. Loadings**	**Proportion var.**	**Cumulative**
Factor 1	8.649	8.323	0.462	0.462	5.408	0.300	0.300
Factor 2	1.380	1.232	0.068	0.531	2.661	0.148	0.448
Factor 3	1.257	1.039	0.058	0.589	2.524	0.140	0.589

From the table above, the characteristics of the factors before and after rotation are presented. The table provides the following information:

- Eigenvalues: These determine the factors retained for analysis. Only factors with eigenvalues equal to or greater than one are included, with larger eigenvalues indicating more significant factors.

- Unrotated Solution: This section displays the sum of squared loadings and the proportion of variance explained by each factor. Specifically, Factor 1 explains 46.2% of the variance, Factor 2 explains 6.8%, and Factor 3 explains 5.8%. The cumulative variance before rotation is also reported.
- Rotated Solution: After rotation, the variance is redistributed among the factors. In this solution, Factor 1 explains 30% of the variance, Factor 2 explains 14.8%, and Factor 3 explains 14%. Overall, three factors (each with an eigenvalue of one or greater) are extracted, which together account for approximately 58.9% (or roughly 60%) of the total variance.

The table below presents the same set of information using the Varimax rotation method.

Table 8.
Factor Characteristics by using Varimax.

Factor Characteristics

		Unrotated solution			Rotated solution		
	Eigenvalues	**SumSq. Loadings**	**Proportion var.**	**Cumulative**	**SumSq. Loadings**	**Proportion var.**	**Cumulative**
Factor 1	6.861	6.475	0.360	0.360	4.254	0.236	0.236
Factor 2	1.533	1.435	0.080	0.439	2.430	0.135	0.371
Factor 3	1.378	1.199	0.067	0.506	2.425	0.135	0.506

From the table above:

- Three factors were extracted, each with a sum of eigenvalues equal to or greater than one. These factors collectively account for 50.6% (approximately 51%) of the total variance.
- The proportion of variance explained using the Varimax rotation is lower than that explained using the Promax rotation.

Table 9.
Correlations matrix of factors using Promax.

	Factor 1	**Factor 2**	**Factor 3**
Factor 1	1.000	0.713	0.686
Factor 2	0.713	1.000	0.624
Factor 3	0.686	0.624	1.000

The table above presents the correlation patterns among the extracted factors, moderate positive correlations are observed between the three factors, aligning with the method's assumption that factors can be interrelated.

Table 10.
Correlations matrix of factors using Varimax.

	Factor 1	**Factor 2**	**Factor 3**
Factor 1	1.000	0.000	0.000
Factor 2	0.000	1.000	0.000
Factor 3	0.000	0.000	1.000

The table above presents the correlation patterns among the extracted factors, correlations between factors are zero, indicating no relationship among them, consistent with the assumption of factor independence in the Varimax method.

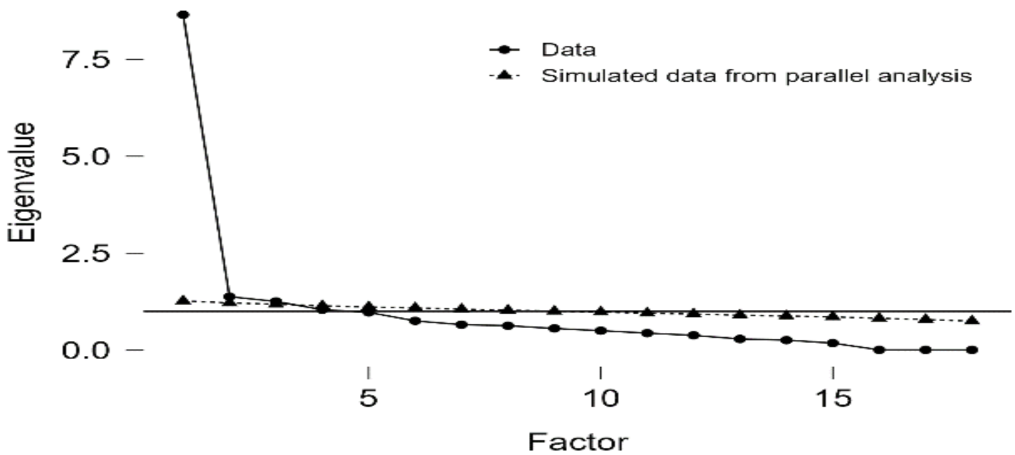

Figure 3.
Path diagram using Promax.

From the Figure aggregations, begin to form between the third and fourth factors. The extracted three-factor solution aligns with the results presented in Table 6, where only factors with eigenvalues greater than 1 are retained.

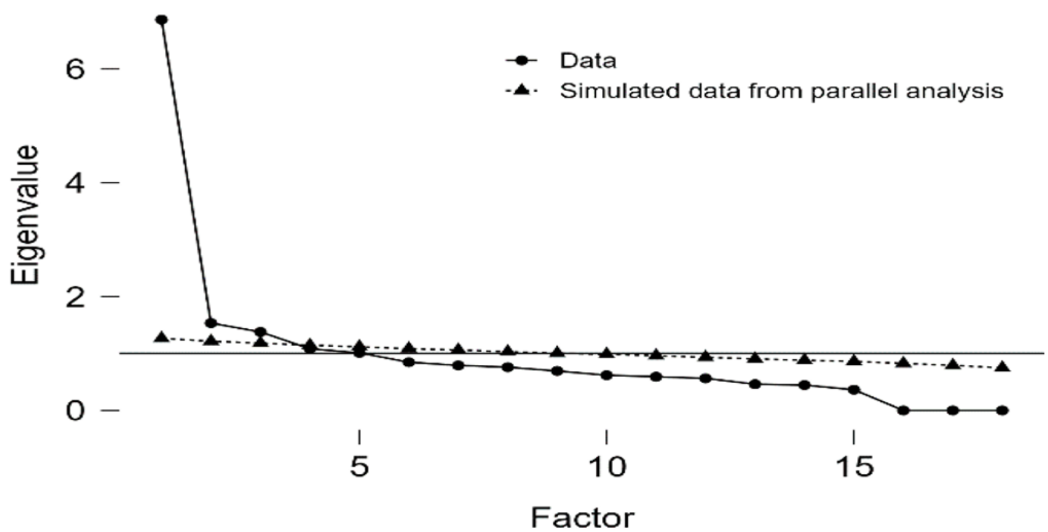

Figure 4.
Path diagram using Varimax.

From the figure above aggregations, appear between the third and fourth factors. The extracted three factors are consistent with the results in Table 7, confirming that only factors with eigenvalues greater than 1 are included in the analysis.

5. Discussion

The comparative analysis of Promax (oblique rotation) and Varimax (orthogonal rotation) in Exploratory Factor Analysis (EFA) provides valuable insights into their respective strengths and applications, particularly when examined in the context of existing literature. The results of the Kaiser-

Meyer-Olkin (KMO) test underscore the superiority of Promax, which achieved an overall Measure of Sampling Adequacy (MSA) of 0.882, compared to Varimax's lower threshold-level score of 0.500. These findings align with Alzayani, et al. [14] who noted that Varimax might be less effective when handling datasets with complex interrelationships, whereas Promax demonstrates higher adequacy and reliability in capturing intricate data structures. Similarly [4] highlighted Promax's advantage in analyzing interrelated variables, a finding supported by the higher MSA scores observed in this study.

The factor correlation matrix further reinforces Promax's capability to capture inter-factor relationships, as indicated by the moderately strong positive correlations ranging from 0.624 to 0.713. This characteristic is consistent with Roy [8] findings, which demonstrated Promax's ability to explore latent constructs with inherent dependencies. By contrast, Varimax produced zero correlations between factors, reflecting its assumption of independence. This feature makes Varimax particularly advantageous in studies prioritizing factor distinctiveness and interpretability, as noted by O'Brien [13].

In terms of variance explained, Promax accounted for 59% of the total variance, outperforming Varimax, which explained 51%. This result corroborates the findings of Corner [12] who observed that oblique rotations, such as Promax, effectively distribute variance across factors, thereby capturing more complex interrelations. Furthermore, these findings support [11] assertion that orthogonal rotations like Varimax may sacrifice some explained variance to preserve factor independence. Promax's superior variance explanation makes it particularly suitable for studies requiring deeper insights into interconnected constructs, as illustrated in dietary and geochemical research by Castro, et al. [4] and Roy [8] respectively.

An analysis of factor saturation further highlights Promax's strength in capturing a greater number of variables per factor. For example, Factor 1 in Promax was saturated by ten variables, compared to nine in Varimax. Factors 2 and 3 in Promax each included one additional variable relative to their Varimax counterparts. These results align with Castro, et al. [4] findings, which suggest that Promax is more sensitive in identifying subtle contributions of variables across multiple factors. While Varimax provides clarity by preventing cross-loadings, as noted by Alzayani, et al. [14] this characteristic may limit its applicability in studies involving complex datasets with overlapping constructs.

The eigenvalues and factor characteristics further emphasize Promax's ability to balance the redistribution of variance post-rotation. Promax achieved a more equitable spread of explained variance across the three factors, with Factor 1 contributing 30%, and Factors 2 and 3 contributing 14.8% and 14%, respectively. In contrast, Varimax displayed a less balanced distribution, with Factor 1 accounting for 23.6%, followed by Factors 2 and 3 at 13.5% each. This finding mirrors [7] conclusion that Promax provides a more balanced representation of variance, which is particularly beneficial for studies aiming to uncover complex data patterns.

Overall, the differences between Promax and Varimax reflect their distinct methodological foundations and strengths. Promax, which assumes correlations between factors, is more appropriate for datasets with interrelated latent constructs [8, 12]. In contrast, Varimax is better suited for exploratory studies requiring factor independence and simplicity [11, 13]. The results of this study particularly Promax's higher reliability, greater variance explained, and superior factor saturation reinforce its utility in multidimensional analyses. At the same time, Varimax remains a robust choice for datasets requiring clearly distinct and independent factor structures.

These findings contribute to a broader understanding of factor rotation techniques by emphasizing the need to align the choice of method with the dataset's characteristics and the study's objectives. While Promax excels in capturing complex interrelationships, Varimax provides a clear and straightforward interpretation of independent factors. Future research should extend these comparisons by applying both methods across diverse fields and datasets of varying complexity to further validate and refine these conclusions.

6. Conclusion

The study concluded that the oblique rotation method, Promax, offers greater reliability than the orthogonal Varimax rotation in Exploratory Factor Analysis (EFA), particularly in enhancing the interpretability of factors influencing academic achievement. Using data from 394 university students in Saudi Arabia, the study assessed the performance of these rotation methods in terms of factor extraction, variance explained, and interpretability.

The findings indicate that Promax, an oblique rotation technique, is more effective in handling interrelated constructs, offering higher reliability and explaining a greater proportion of variance compared to Varimax. Additionally, Promax demonstrated its ability to capture moderate correlations between factors, providing deeper insights into complex data structures. In contrast, Varimax, which assumes factor independence, produced a clearer but less nuanced interpretation.

The study recommends using Promax for analyzing datasets with interrelated constructs, as it provides a more comprehensive and realistic representation of relationships. Conversely, Varimax remains a valuable choice for studies requiring orthogonal factors and straightforward interpretations.

Future research should expand this comparison by examining these rotation techniques across various disciplines and larger, more diverse datasets. Additionally, integrating these methods with advanced computational tools could further refine their applicability, ensuring robust methodological choices tailored to specific research objectives.

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Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Appendix 1.
Questionnaire.

Q	**Phrase**
Q1	Use the memorization method
Q2	Students not realizing the value of university studies and underestimating it.
Q3	Frequent student absence from lectures
Q4	Difficulty comprehending some courses of programs
Q5	The weakness of some students' level of English before joining the university
Q6	Lack of competencies among faculty members
Q7	Weak family censorship for sons
Q8	Lack of communication between students and the department they belong to.
Q9	Family problems within the family
Q10	The student's preoccupation with meeting the needs of the family
Q11	High cost of access to university
Q12	Fear while taking the exam
Q13	Lack of focus during lectures
Q14	Admission to majors without personal desire
Q15	Inability to organize time
Q16	Crowded students in the class
Q17	After housing from the university and the difficulty of transportation by transportation
Q18	The high costs of references and study attachments