Abjadia : International Journal of Education, 11 (1): 337-348 (2026)
DOI: 10.18860/abj.v11i1.36003

2443-0587 (ISSN Online)
2528-3979 (ISSN Print)
abjadia International Journal of Education
أبجدية مجلة عالمية دولية في التربية
Research and Publication Center
Tarbiyah and Teaching Training Faculty
State Islamic University of Maulana Malik Ibrahim
Malang Indonesia
http://ejournal.uin-malang.ac.id/index.php/abjadia
e-mail: abjadia@uin-malang.com

IDENTIFYING MOTIVATIONAL FACTORS IN NAHWU COURSES USING PRINCIPAL COMPONENT ANALYSIS (PCA): A STUDY OF ARABIC LANGUAGE EDUCATION STUDENTS

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Abstract

The challenges faced by students in studying Nahwu, an essential component of the Arabic language, often relate to the complexity of its rules, making it feel difficult and diminishing learning motivation. This study aims to analyze the factors influencing students' learning motivation in Nahwu courses at the university level, offering solutions through a deeper understanding of intrinsic motivation, extrinsic motivation, and amotivation. The research employed a descriptive quantitative method with factor analysis using Principal Component Analysis (PCA). Data were collected over a one-month period via questionnaires from 46 fifth-semester students (cohort 2020) in the Arabic Language Education Program at UIN Datokarama Palu. The motivation indicators employed in this study were based on the Academic Motivation Scale (AMS) developed by Robert J. Vallerand, which comprises seven distinct indicators. The findings reveal two main factors affecting learning motivation: the Self-Regulation Factor, which is associated with positive motivation, and the Helplessness Factor, reflecting feelings of inability. These findings are expected to provide insights for educators in creating effective teaching methods to enhance students' motivation and learning outcomes in Nahwu courses.

Keywords: Principal Component Analysis, Learning Motivation, Nahwu, Self-Determination Theory, Higher Education

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Article History	Received	Revised	Accepted	Published
	2025-08-08	2026-01-03	2026-01-23	2026-03-15

INTRODUCTION | مقدمة

Nahwu is an essential part of learning Arabic and is considered a fundamental basis for studying the language. As a key to understanding various Islamic literature, such as the Qur'an and Hadith, Nahwu facilitates access to these foundational texts. This urgency is further reinforced by the curriculum standards in State Islamic Higher Education (PTKIN), which mandate the mastery of Arabic linguistic components, including Nahwu, as a core competency for students in the Arabic Language Education program. However, many learners often face difficulties in studying Nahwu, primarily due to its complex and perceived complicated rules (Supardi et al., 2022). These challenges can lead to frustration, lower motivation to learn, and reduced confidence in mastering the material. Therefore, it is crucial to address these obstacles to maintain learners' motivation and help them better understand Nahwu.

Learning motivation is a crucial factor that plays a significant role in determining the success of the learning process (Candra et al., 2023). Generally, motivation is often associated with enthusiasm (Yogi Fernando et al., 2024). It is defined as the process of initiating and

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sustaining activities focused on achieving goals. In the expectancy-value theory, motivation is a function of the expectations of success and the value that individuals place on the task (Cook & Artino, 2016).

One of the primary theories used to understand motivation is the Self-Determination Theory (Deci & Ryan, 1985). Recent meta-analyses confirm that this framework remains robust in predicting student outcomes across various educational contexts (Howard et al., 2021). This theory distinguishes between three types of motivation: intrinsic motivation, extrinsic motivation, and amotivation. Intrinsic motivation refers to the drive to engage in an activity due to personal satisfaction and interest; extrinsic motivation relates to the drive stemming from external factors, such as rewards or recognition; while amotivation describes a condition where individuals lack the desire or intention to act (Vallerand, 1992)

Motivation is often divided into two types: intrinsic motivation and extrinsic motivation (Harandi, 2015). Intrinsic motivation comes from within the individual, while extrinsic motivation is driven by external factors. Extrinsic motivation originates from outside influences that affect a person's behavior in their life. These external prompts encourage individuals to cultivate and enhance their intrinsic motivation, leading to a transformation of their current attitudes toward a more positive direction (Hamdani et al., 2020).

In contrast to the view expressed by (Rheinberg & Engeser, 2018) the term "intrinsic" can be used to describe motivation that originates directly from the activity itself. In other words, intrinsic motivation is the drive that arises from the enjoyment or satisfaction derived from engaging in a particular activity. Conversely, "extrinsic" motivation comes from the outcomes or benefits gained after completing the activity. The distinction between intrinsic and extrinsic motivation is based on their processes: "intrinsic" relates to the sense of fulfillment experienced while performing the activity, whereas "extrinsic" is associated with the goals or end results one aims to achieve.

Although intrinsic and extrinsic motivation can occur simultaneously within an individual while completing a task, they remain distinct dimensions of motivation, with one typically having a greater influence (Kuvaas et al., 2017). This indicates that while they can complement each other, certain conditions or contexts often make one type of motivation more dominant, which in turn can affect how individuals approach and complete the task. For instance, in situations where individuals are highly interested in the activity, intrinsic motivation tends to be stronger, whereas in contexts where external rewards are more prominent, extrinsic motivation may take precedence.

In addition to intrinsic and extrinsic motivation, (Deci & Ryan, 1985) also introduced amotivation as a third type within the motivation construct. Amotivation occurs when individuals feel that there is no connection between their actions and the outcomes achieved, resulting in a lack of motivation both intrinsically and extrinsically. Individuals experiencing amotivation often feel incompetent, hold low expectations of their abilities, and feel powerless because they perceive their behaviors as being influenced by external factors. This condition can lead to doubts about educational goals and cause them to withdraw from academic activities.

Amotivation, which literally means "lack of motivation," describes an apathetic attitude towards motivation, where students lack sufficient reasons or drives to invest energy and effort in the learning process or to achieve specific goals. In the classroom context, students experiencing amotivation tend to be passive, may fall asleep, skip classes, or merely pretend to participate. They often just "go through the motions" of class tasks without truly engaging in the learning activities (Cheon & Reeve, 2015).

Previous research has shown that motivation and learning outcomes in Nahwu and Sharaf are influenced by internal factors such as memory, interest in learning, and diverse educational backgrounds, as well as external factors like teaching methods, learning environments, and family support (Syarifaturrahmatullah et al., 2023). Another study conducted at the Pesantren Luhur Malang found that an inductive teaching method based on examples effectively enhances motivation and learning outcomes in Nahwu, making the subject more engaging and relevant for students (Rifa'i & Khasairi, 2023).

This study aims to expand the understanding of the factors influencing student motivation in Nahwu courses at the college level. Unlike previous studies that have emphasized teaching methodologies or general motivational conditions, this research focuses on specific internal and external factors impacting student motivation in higher education contexts. Consequently, the primary objective of this study is to determine the latent motivational factors underlying students' engagement in Nahwu courses at the university level.

METHOD | منهج

This study use a quantitative research method, focusing on the structured collection and analysis of data that can be numerically represented (Goertzen, 2017), In other words, quantitative research uses various methods aimed at testing specific theories or hypotheses by relating multiple variables (Fikri et al., 2024). The type of research conducted is descriptive quantitative, which provides a systematic framework for answering a problem through stages of research that utilize a quantitative approach (Harahap, 2020).

Participants and Data Collection The population in this study consists of 87 students from the Arabic Language Education Study Program (PBA) of the 2021 cohort at UIN Datokarama Palu. The sample was determined using the Stratified Random Sampling technique, resulting in a final sample size of 46 participants. The data used in this research is primary data collected through questionnaires. The instrument construction was based on the Academic Motivation Scale (AMS) derived from the Self-Determination Theory developed by Robert J. Vallerand et al. (Vallerand, 1992):, which consists of seven distinct motivational sub-scales.Data Analysis The data analysis was conducted using IBM SPSS Statistics software. Before performing the factor analysis, the instrument underwent validity and reliability testing to ensure the items accurately measured the intended constructs. Items that did not meet the validity criteria (loading factor < 0.3) were excluded to maintain the integrity of the instrument.

Table 1. Learning Motivation Questionnaire Indicators

Factor		Indicator
Motivation	Intrinsic	(X1) To know
		(X2) To achieve
		(X3) To experience stimulation
	Extrinsic	(X4) External regulation
		(X5) Introjected regulation
		(X6) Identification
	Amotivation	(X7) Feeling of inadequacy

Data in this study is analyzed using factor analysis. The basic concept of factor analysis is to identify the relationships between several variables to form a smaller group of variables than the initial number. This approach aims to simplify the interpretation of existing phenomena. The new variables generated from this analysis are generally referred to as factors or latent variables (Asra et al., 2017).

Factor analysis in this study utilizes a data dimension reduction method known as Principal Component Analysis (PCA). PCA is a statistical technique aimed at reducing data dimensions by extracting the main factors from a model. In applying this method, we work with a correlation matrix that has a value of one on its diagonal.

The primary objective of Principal Component Analysis (PCA) is to identify factors that can explain as much variation in the data as possible. Each factor generated seeks to account for the majority of the variation in the correlation matrix used. Through this approach, we aim to understand the relationships among the existing variables. However, in practice, not all identified factors are utilized, as many may be less important or insignificant, leading to the consideration of only the most relevant factors for further analysis (Gorsuch, 2015).

The stages of the Principal Component Analysis (PCA) test according to (Wangge, 2021) are as follows:

1. Testing the specified variables using the KMO (Kaiser-Meyer-Olkin) method and Bartlett's Test. KMO is a technique in factor analysis used to evaluate the feasibility of data by measuring the appropriateness of the correlation matrix among variables for the proposed factor model. KMO values range from 0 to 1, with higher values indicating that the data is more suitable for factor analysis (Abimanyu & Mahendra, 2024). If the KMO value is greater than 0.5, factor analysis can be conducted (Arisandi et al., 2022). Bartlett's Test is used to assess the significance of correlations among variables, allowing for further analysis through factor analysis (Asra et al., 2017).
2. Measure Sampling Adequacy (MSA) testing is a prerequisite test used to assess the strength of relationships among the variables involved in factor analysis. This test also determines whether the variables from each analyzed dataset meet the criteria for further analysis (Sunarmi et al., 2022). In other words, the MSA test is used to evaluate the degree of partial correlation among the variables. The MSA results are measured on a scale from 0 to 1, with a criterion set at MSA > 0.5 (Fardani et al., 2021).
3. Conducting the factoring process, which involves deriving one or more factors from the variables tested in the second step. This stage involves extracting and deriving main factors from the variables. The number of factors formed is determined by examining eigenvalues greater than one (Eigenvalue > 1), which indicates the factor explains significantly more variance than a single variable.
4. Estimating factor weights (factor loading) and rotation. After extraction, factor loadings are examined to determine the correlation between variables and factors. To clarify these relationships and simplify interpretation, orthogonal rotation using the Varimax method is employed. This technique maximizes the variance of the squared loadings, ensuring each variable correlates strongly with only one factor.
5. Factor scores are measures that indicate the representativeness of a variable by each factor, serving as raw data for further analysis. They can also be referred to as composite measures for each factor across individual objects.

RESULT | نتائج

After undergoing the validity and reliability testing phase, the researcher found that there are 33 valid questionnaire items to be used in this study. The reliability test results indicated a value of 0.781, which falls within the high reliability category. This demonstrates that the instruments used are sufficiently consistent and reliable for measuring the variables under investigation.

This study aims to examine the factor structure of the learning motivation instrument adapted from the Self-Determination Theory (Vallerand, 1992). To validate the grouping of items into intrinsic, extrinsic, or amotivation dimensions, an Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis (PCA) extraction and Varimax orthogonal rotation. The stages of the Principal Component Analysis (PCA) test are as follows:

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.753
Bartlett's Test of Sphericity	Approx. Chi-Square	83.077
	df	21
	Sig.	.000

Figure 1. Results Of The KMO (Kaiser-Meyer-Olkin) Test And Bartlett's Test

The first step involves determining questions that represent each indicator of the variables, which are then tested using the KMO (Kaiser-Meyer-Olkin) method and Bartlett's Test. The initial step in factor analysis involves verifying whether the correlation matrix between variables is sufficient for extraction. The variables were first tested using the KMO (Kaiser-Meyer-Olkin) method and Bartlett's Test.

Correlation Matrix[a]

		X1	X2	X3	X4	X5	X6	X7
Correlation	X1	1.000	.483	.498	.218	.428	.282	-.214
	X2	.483	1.000	.584	.244	.343	.286	-.186
	X3	.498	.584	1.000	.536	.443	.378	-.260
	X4	.218	.244	.536	1.000	.472	.405	-.056
	X5	.428	.343	.443	.472	1.000	.338	.082
	X6	.282	.286	.378	.405	.338	1.000	.046
	X7	-.214	-.186	-.260	-.056	.082	.046	1.000
Sig. (1-tailed)	X1		.000	.000	.073	.002	.029	.077
	X2	.000		.000	.051	.010	.027	.109
	X3	.000	.000		.000	.001	.005	.041
	X4	.073	.051	.000		.000	.003	.357
	X5	.002	.010	.001	.000		.011	.294
	X6	.029	.027	.005	.003	.011		.381
	X7	.077	.109	.041	.357	.294	.381	

a. Determinant = ,137

Figure 2. Results Of The Correlation Matrix

Figure 1 above indicates that at a 95% confidence level, the data is suitable for factor analysis, as the KMO value obtained ranges from 0.7 to 0.753, falling within the range of 0.7 ≤ KMO ≤ 0.8. According to (Hair, 2009), a KMO value above 0.50 is acceptable, and values in the range of 0.70–0.80 are categorized as 'Meritorious'. This suggests that factor analysis is appropriate for the data used. Furthermore, the results of Bartlett's Test show a significant outcome, where $p < \alpha$ (0.05), indicating that the variables used have a sufficient correlation to be analyzed through factor analysis. To further ensure the data's suitability, the correlation matrix was examined. The results show that most variables are significantly correlated, satisfying the requirements for factor analysis.

The second step involves the Measure Sampling Adequacy (MSA) test, which is used to determine the degree of partial correlation among the variables. The following matrix represents the partial correlations between the variables, illustrating the relationships among them.

Anti-image Matrices

		X1	X2	X3	X4	X5	X6	X7
Anti-image Correlation	X1	.778[a]	-.218	-.206	.150	-.294	-.105	.170
	X2	-.218	.785[a]	-.401	.123	-.080	-.081	.040
	X3	-.206	-.401	.752[a]	-.396	-.095	-.099	.211
	X4	.150	.123	-.396	.694[a]	-.312	-.233	.029
	X5	-.294	-.080	-.095	-.312	.764[a]	-.057	-.240
	X6	-.105	-.081	-.099	-.233	-.057	.849[a]	-.138
	X7	.170	.040	.211	.029	-.240	-.138	.512[a]

a. Measures of Sampling Adequacy(MSA)

Figure 3. Results Of The Measure Sampling Adequacy (MSA) Test

Based on the results in the matrix above, it is evident that the MSA values for each variable exceed 0.5. This indicates that the data used is adequate and that all variables are suitable for factor analysis. Since all variables met the necessary criteria, none of the variables needed to be discarded. This signifies that each variable contributes significantly to the overall analysis, allowing all variables to be retained in the model to ensure the analysis encompasses all relevant aspects of the phenomenon being studied.

The third step in this analysis involves testing the Measure Sampling Adequacy (MSA) from the second stage for all variables involved. After conducting the MSA test, the results indicate that all variables meet the necessary criteria, meaning that none of the variables need to be discarded. This signifies that each variable contributes significantly to the overall analysis, allowing all variables to be retained in the model. By not discarding any variables, we ensure that the analysis encompasses all relevant aspects of the phenomenon being studied, resulting in more comprehensive and accurate outcomes.

In the fourth step, factor loading estimation aims to determine the number of factors that will be formed by examining eigenvalues greater than one. Before assessing the eigenvalues, the factor analysis employs Principal Component Analysis (PCA) to reduce the data dimensions, simplifying the structure of the data. This simplification facilitates easier interpretation of a situation involving multiple variables

Communalities

	Initial	Extraction
X1	1.000	.556
X2	1.000	.578
X3	1.000	.730
X4	1.000	.552
X5	1.000	.608
X6	1.000	.497
X7	1.000	.724

Extraction Method: Principal Component Analysis.

Figure 4. The Result Of Factor Analysis Employs Principal Component Analysis

The figure above illustrates the extent to which the variability of each variable in the factor analysis can be explained by the extracted factors. Notice the "extraction" column, which indicates the amount of variability each variable successfully explained by the factors after the extraction process is completed. A variable is considered capable of explaining a factor if the extraction value is greater than 0.50. Based on the results in the table, there is one variable that falls below the 0.5 threshold, indicating that less than half of its variability can be explained by the extracted factors. In the context of factor analysis, this is considered low, as it is generally expected that communalities should be above 0.5 to demonstrate that the extracted factors can explain most of the variability of those variables.

The following figure is used to determine how many relevant factors exist and the extent to which each factor contributes to explaining the data. The "initial eigenvalues" column shows the total variance explained by each factor before rotation, measured by eigenvalues. Factors with eigenvalues greater than 1 are typically retained, as this indicates that the factor explains more variance than a single original variable.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.034	43.349	43.349	3.034	43.349	43.349
2	1.212	17.311	60.661	1.212	17.311	60.661
3	.810	11.574	72.235			
4	.673	9.618	81.852			
5	.570	8.140	89.993			
6	.401	5.730	95.722			
7	.299	4.278	100.000			

Extraction Method: Principal Component Analysis.

Figure 5. The Result Of Eigenvalues

Based on the results in the table above, two factors were obtained with eigenvalues greater than 1: component 1 (3.034) and component 2 (1.212). According to the rule of eigenvalues greater than 1, only these two factors are retained to explain the variance in the data. Factors beyond component 2 have eigenvalues below 1, indicating that they are not significant for further analysis. These two components together explain 60.661% of the total variance (as shown in the Cumulative % column). This means that approximately 60.6% of the variability in the data can be explained by these two factors, which is quite satisfactory for data representation in factor analysis. To further confirm the number of factors formed, the Scree Plot was examined. The plot displays the eigenvalues plotted against the number of components.

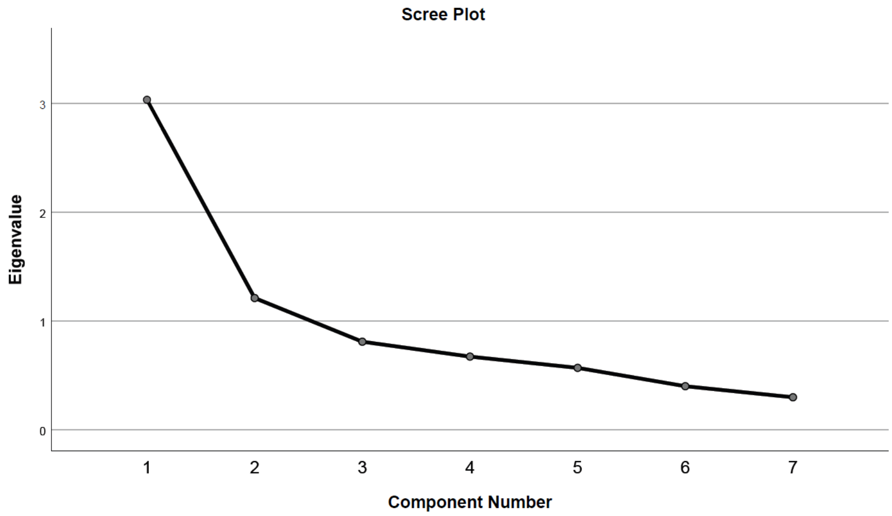

Figure 6. Scree Plot

As shown in the Scree Plot, there is a sharp decline (an "elbow") after the second component, after which the curve flattens. This visual confirmation supports the decision to retain two factors for further rotation and interpretation.

The next step is to facilitate interpretation and minimize ambiguity in item placement, factor rotation was performed using the Varimax method. This rotation maximizes the variance of the squared loadings, resulting in a clearer distribution of items. The results of the rotated component matrix are presented below.

Rotated Component Matrix[a]

	Component	
	1	2
X1	.395	.633
X2	.395	.650
X3	.576	.631
X4	.728	.150
X5	.767	.143
X6	.702	.066
X7	.324	-.787

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 3 iterations.

Figure 7. The Result Of Factor Score Component Matrix After Rotated

The component matrix table above displays the detailed results of the factor analysis after rotation, linking each variable to the generated components. The values shown are factor loadings, which represent the correlation coefficients between the original variables and the identified factors. A higher absolute value (closer to 1) indicates a stronger relationship between the variable and the factor.

Based on the rotated matrix in Figure 7, a clear grouping of items is observed. The distribution of factor loadings for each indicator is summarized in the table below:

Table 2. Results From Indicator Factoring

Factor	Loading	Indicator
1	0.767	(X5) Introjected Regulation
	0.728	(X4) External Regulation
	0.702	(X6) Identification
2	0.650	(X2) To Achieve
	0.633	(X1) To Know
	0.631	(X3) To Experience Stimulation
	-0.787	(X7) Feeling of Inadequacy

The final stage involves naming the new factors. Based on the relationships among the analyzed variables, the first factor is named Self-Regulation Factor, as it encompasses variables related to self-regulation. The factor loading values indicate a strong connection between these variables and this factor. As observed in Table 2, the variables are distinctly distributed into two components. Factor 1 is dominated by variables associated with external regulation types (X4, X5, X6), while Factor 2 is characterized by variables associated with intrinsic motivation (X1, X2, X3) and amotivation (X7).

DISCUSSION | مناقشة

Based on the rotated matrix (Figure 7) and the summary in Table 2, the seven indicators are polarized into two distinct psychological dimensions:

Factor 1: Extrinsic Motivation Dimension

The first factor is consistently formed by indicators X4 (External Regulation), X5 (Introjected Regulation), and X6 (Identification). The factor loading values range from 0.702 to 0.767, indicating a strong contribution. These findings align with the Self-Determination Theory (SDT) framework, where these three indicators represent drives stemming from outside the individual or the internalization of external norms.

This grouping suggests that a significant portion of student motivation is driven by the desire to meet external standards or to avoid guilt. This aligns with findings by Hadi (Hadi, 2020), who emphasizes that learning motivation is closely linked to self-regulation, where students actively manage their behaviors and cognitive processes to achieve academic targets, often driven by external expectations or internalized values. In this context, students regulate their study habits in Nahwu not solely out of pure interest, but to maintain self-worth or achieve grades, demonstrating a form of regulated motivation.

Factor 2: Intrinsic Motivation & Amotivation Dimension

The second factor comprises indicators X1 (To Know), X2 (To Achieve), X3 (To Experience Stimulation), and X7 (Amotivation). Within this dimension, two interesting statistical phenomena require detailed interpretation.

First, indicator X3 (To Experience Stimulation) exhibits considerable factor loadings on both components (0.576 on Factor 1 and 0.631 on Factor 2); however, the decision to assign X3 to Factor 2 is justified both statistically, as the loading is higher ($0.631 > 0.576$), and theoretically, since "seeking stimulation or pleasure" is the core of intrinsic motivation, making it conceptually more relevant to the Intrinsic group.

Second, item X7 (Feeling of Inadequacy) shows a very strong but negative loading (-0.787). This negative polarity is not an error but a significant finding regarding construct validity, as Factor 2 represents "Internal Orientation." Since X7 measures amotivation (lack of intention or feeling of incompetence), it logically has an inverse correlation with the intrinsic factor. This implies that respondents who score high on Factor 2 (highly intrinsically motivated) tend to score very low on indicator X7 (low amotivation), meaning they feel capable and confident. This relationship is supported by Ardyansyah et al. (2020), who state that self-efficacy plays a crucial role in learning; students who believe in their capabilities (high self-efficacy) are less likely to feel inadequate or amotivated. Conversely, the absence of intrinsic drive is strongly associated with feelings of powerlessness. Thus, this factor effectively captures the "Self-Determined" aspect of motivation, where high scores indicate strong intrinsic drive and high self-efficacy.

CONCLUSSION | خاتمة

Based on the theoretical framework, student motivation in Nahwu courses is comprised of three core constructs: intrinsic motivation, extrinsic motivation, and amotivation. Intrinsic motivation arises from within the student, driven by curiosity and the desire to master the subject. Extrinsic motivation involves external influences, such as grades, lecturer support, and rewards. Meanwhile, amotivation represents a state of powerlessness or a lack of intention to learn, often stemming from perceived incompetence or negative experiences.

The factor analysis conducted in this study, however, simplifies these constructs into two dominant latent components. The first component, the Extrinsic Motivation Dimension, highlights that a significant portion of student engagement is regulated by external standards and the desire for achievement. The second component, the Intrinsic Motivation & Amotivation Dimension, uncovers a critical inverse relationship: strong intrinsic motivation effectively neutralizes feelings of inadequacy (amotivation). This finding implies that "powerlessness" in learning Nahwu is not an isolated state but rather the absence of intrinsic drive. Consequently, to minimize amotivation and enhance student success, educators should not only provide external incentives but, more importantly, employ teaching strategies that stimulate students' internal interest and self-efficacy.

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