Online Learning in Educational Research
Volume 5, Issue 2, 395-409.
e_ISSN: 2798-2351
https://www.journal.foundae.com/index.php/oler/index
DOI: 10.58524/oler.v5i2.835

Digital Achievement Motivation Scale for Mathematics Learning: Validity, Reliability, and Micro Testing Evidence

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Article Info

Article history:

Received: July 19, 2025
Revised: November 25, 2025
Accepted: December 4, 2025

Keywords:

Achievement Motivation;
Digital Questionnaire;
Mathematics Learning;
Scale Instruments.

Abstract

Achievement motivation plays a crucial role in students' success in mathematics learning, yet valid and practical measurement instruments are still limited, especially those that utilize digital questionnaire platforms. This study aims to develop an Achievement Motivation Scale for High School Students in Mathematics Learning using a digital questionnaire platform. The research method used is the ADDIE development model, which includes the stages of analysis, design, development, implementation, and evaluation. A total of 30 items were constructed from five motivational dimensions and validated by 3 experts, resulting in 24 valid items (86.7%) and six revised items. Usability testing involving three Information Technology experts, three teachers, and three students yielded average scores of 73%, 93.3%, and 86.7%, respectively, indicating the instrument is user-friendly and well-received. Field testing with 57 students revealed 14 items met the discrimination index ($r \geq 0.30$). Exploratory factor analysis showed factor loadings between 0.40–0.85, supporting construct validity. Reliability testing using Cronbach's Alpha yielded 0.89, indicating high internal consistency. Thus, 14 items were declared valid, reliable, and practical for measuring achievement motivation in mathematics learning using a digital platform.

To cite this article: Widyastuti, S. R. (2025). Digital achievement motivation scale for mathematics learning: Validity, reliability, and micro testing evidence. *Online Learning in Educational Research, 5*(2), 395-409. https://doi.org/10.58524/oler.v5i2.835

INTRODUCTION

Mathematics is often perceived as a difficult and challenging subject by students (Bichi et al., 2018; Deogratias & Iddi, 2025; Rizal et al., 2023; Zanabazar et al., 2023). This is reflected in a preliminary survey of 100 high school students in Cirebon, which found that 65% of students reported difficulty understanding mathematical concepts due to low learning motivation. These results are consistent with previous research showing that student motivation significantly affects their performance and persistence in learning mathematics (Hossein-Mohand & Hossein-Mohand, 2023; Wu et al., 2022). In addition, group discussions with mathematics teachers revealed that students' low motivation is often linked to a lack of drive to achieve, which aligns with empirical studies indicating that competence satisfaction, autonomous motivation, intrinsic value, and self-concept significantly contribute to students' academic performance in mathematics (Liou et al., 2024; Wang et al., 2022), This low motivation is also evident in student learning outcomes, as reflected by students' reduced confidence in solving mathematical problems and increased academic procrastination (Wisudawati & Kirana, 2022). Such procrastination is further reinforced by anxiety when students face evaluations or academic pressure, particularly in mathematics learning (Chavez-Yacolca et al., 2025; Fernanda & Lidiawati, 2025).

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McClelland (1961) highlighted achievement motivation as a key factor that encourages individuals to strive for success and exceed expected standards. This motivation plays a vital role in supporting student learning (Firman et al., 2024; Mahmud et al., 2023; Widarti et al., 2024). Research by Prast et al. (2018) shows that students with high achievement motivation tend to have better academic outcomes. However, interviews with 10 mathematics teachers and 30 high school students in Cirebon revealed that there is no valid, reliable, and specific tool available to measure achievement motivation in mathematics learning, particularly in digital form via online questionnaire platforms like Google Forms. This finding is in line with previous studies reporting that instruments for measuring students' motivation, especially in the context of mathematics, remain limited and are rarely developed in digital formats (Liou et al., 2024; Wang et al., 2022).

Instruments for measuring students' motivation are crucial in modern learning, particularly in mathematics education, where motivation strongly determines students' persistence, effort, and achievement. Accurate measurement is essential because, without valid and reliable instruments, teachers and researchers cannot identify students' motivational profiles, design appropriate interventions, or monitor changes in learning behavior. To address this need, the development of a well-structured, theory-based measurement tool is essential. Scales play a crucial role in structuring quantitative data along specific dimensions, which is fundamental in developing valid educational instruments (Buntins et al., 2021; Kerlinger, 1966). Previous scholars have emphasized that well-designed scales enable precise measurement of psychological and behavioral attributes (Azwar, 2004; DeVellis & Thorpe, 2021). In mathematics education, such structured instruments are particularly important for capturing latent constructs across different dimensions and generating accurate, efficient, and applicable data to support educational interventions, especially in increasingly digital learning contexts (Saadati & Celis, 2022)

While well-constructed scales are essential for accurately measuring students' achievement motivation, their effectiveness also depends on how they are administered, particularly in increasingly digital learning contexts. A digital questionnaire platform is a technology-based system that facilitates the compilation, distribution, and collection of survey data online. Previous studies highlight that web-based survey platforms enable structured and automated data collection, simplify research procedures, and improve efficiency (Maymone et al., 2018; Mohorko & Hlebec, 2016). In addition, digital questionnaire systems provide flexible design options and easy access through various devices, enhancing respondent engagement and data quality (Revilla & Ochoa, 2017) Consequently, digital platforms are increasingly adopted in educational research due to their capacity to support rapid data collection and real-time monitoring, making them highly relevant for motivation assessment in mathematics learning (Evans & Mathur, 2018)

Several instruments have been developed to measure achievement motivation, such as the Academic Motivation Scale (Vallerand et al., 1992) and the Achievement Motivation Inventory (Schuler & Thorn, 2002). However, recent literature demonstrates a strong shift toward developing more contextualized measurement tools that capture motivational dynamics within specific learning domains. For example, Toohey et al. (2025) validated a motivation scale tailored to secondary students' learning experiences, while Esteban et al. (2024) emphasized psychometric development through rigorous EFA and CFA procedures in academic contexts. Similar efforts can be seen in the instruments measuring motivation in STEM fields (Açıksöz et al., 2024) and English listening skills (Hocaoglu & Ocak, 2024). Collectively, these studies highlight the increasing demand for domain-specific motivational instruments rather than broad, generic tools. However, these instruments are generally designed to assess motivation across broad academic contexts and are not specifically tailored to mathematics learning. As a result, they tend to emphasize general achievement or competitive aspects while giving limited attention to domain-specific characteristics of mathematics, such as perseverance in solving complex problems, beliefs about handling abstract concepts, and learning strategies used by students. Therefore, this study seeks to develop a more comprehensive achievement motivation scale that reflects the unique challenges and demands of mathematics learning.

This study aims to develop a digital-based student achievement motivation scale that focuses on mathematics learning at the high school level. This instrument is designed to measure the dimensions of achievement motivation based on McClelland (1961) and Murray & McAdams (2007) theory, using content validity as the main approach to evaluate the validity of the items. The practical benefits of this study are to provide a measuring instrument that can be used by teachers and researchers to identify students' motivation levels more specifically, and can be accessed through a digital questionnaire platform in the context of mathematics learning. In addition to facilitating the process of distributing and collecting data, the digital platform also facilitates efficient analysis of results and allows for more interactive student involvement in the process of filling out the instrument. With this scale, teachers can design more appropriate learning strategies to improve student motivation and achievement. In addition, the measurement results can help educational counselors in providing appropriate interventions for students with low motivation, so that they are more motivated to face academic challenges in mathematics.

METHOD

Research Design and Participants

This study employed a quantitative descriptive method with an instrument development design, using the ADDIE model as the development framework (Branch, 2009). The subjects of the study were 57 students in grade X at a high school in Cirebon (37 female and 20 male).

Instrument Development Based on ADDIE

Analysis

The analysis phase identified the need for an achievement motivation instrument suitable for mathematics learning settings. Five core dimensions of achievement motivation were adopted from McClelland (1961) and Murray & McAdams (2007), namely striving for excellence, desire for feedback, personal responsibility, performing tasks to the best of one's ability, and completing challenging tasks with satisfactory results.

Design

A blueprint was developed using three indicators for each dimension, with two items per indicator, producing 30 items. A three-point Likert scale was used, S (Appropriate), TB (Cannot Determine), TS (Not Appropriate), to indicate whether each statement reflected students' motivational experiences.

Development

Content validity was conducted by two university lecturers and one mathematics teacher. Experts assessed the item–indicator suitability with the percentage agreement method, where items scoring above 50% were retained while others were revised. Validated items were digitized using Google Forms to produce the operational version of the instrument.

Implementation

Usability testing was performed with IT experts, teachers, and students, focusing on platform accessibility, clarity of instructions, time efficiency, clarity of statements, and user motivation. A pilot test was then completed by 57 students to generate empirical data for psychometric analysis.

Evaluation

The evaluation stage focused on empirical verification of item quality and instrument feasibility. All items were tested for discrimination, construct validity, and internal consistency. The validated items and statistical results formed the basis of the finalized scale. (Azwar, 2004).

Data Analysis Procedures

Content Validity

Content validity was assessed by three experts (two lecturers and one mathematics teacher). The analysis employed the *percentage of agreement* formula:

$$P = \frac{f}{N} \times 100\%$$

Where f is the number of agreements, and $Nwhat$ is the total possible number of agreements? An item was considered valid if the percentage of agreement exceeded 50%. Items below the threshold were revised.

Usability Testing

Usability testing was conducted with three IT experts, three teachers, and three students. The criteria evaluated included: a. ease of access to Google Forms; b clarity of instructions; c. time efficiency; d. clarity of statements; and e. motivation when completing the digital instrument.

Item Discrimination Analysis

Item quality was tested using the corrected item–total correlation coefficient. An item was considered to have satisfactory discrimination power if the correlation was:

$$r \geq 0.30$$

Items below this threshold were eliminated or revised (Azwar, 2004).

Construct Validity

Construct validity was tested using Exploratory Factor Analysis (EFA). The requirements for EFA were Kaiser-Meyer-Olkin (KMO) value > 0.50 and Bartlett's Test of Sphericity with significance $p < 0.05$. Items with factor loadings ≥ 0.40 were retained.

Reliability Testing

Reliability was assessed using Cronbach's Alpha to determine internal consistency, with the formula:

$$\alpha = \frac{k}{k-1}(1 - \frac{\sum \sigma_i^2}{\sigma_t^2})$$

Here k= number of items, σ_i^2= item variance, and σ_t^2= total variance. An alpha value ≥ 0.70 indicated that the instrument was reliable.

Response Tabulation and Midpoint Calculation

Furthermore, $Mindpoint_i$ refers to the midpoint of the cumulative proportion, calculated by taking half of the proportion for the respective response category and adding it to the cumulative proportion of all categories to its left:

$$Mindpoint_i = \frac{1}{2}p_i + \sum_{j-1}^{i-1} p_j$$

Where:
p_i= the proportion of responses in the i-th response category
$\sum_{j-1}^{i-1} p_j$= the cumulative proportion of responses in all categories preceding the i-th category
$Mindpoint_i$= the midpoint of the cumulative proportion for the i-th response category

Score Categorization

The achievement motivation levels were categorized into low, medium, and high, based on the mean (μ) and standard deviation (σ), following Azwar (2004). The categorization formula in Table 1.

Table 1. Score Category Guidelines Based on Mean and Standard Deviation (Category Norm/Statistical Norm)

Score Range (X)	Motivation Level
$X < (\mu - 1{,}0\sigma)$	Low
$(\mu - 1.0\sigma) \leq X < (\mu + 1{,}0\sigma)$	Medium
$(\mu + 1{,}0\sigma) \leq X$	High

RESULTS AND DISCUSSION

The development of a digital-based achievement motivation scale instrument for senior high school students in mathematics learning was carried out through a systematic process, including the preparation of a blueprint, item construction, content validation, usability testing, participant response analysis, item discrimination analysis, construct validity testing, reliability testing, and score interpretation. The results of each stage are summarized as follows.

Instrument Blueprint.

The blueprint of the developed instrument is presented in Table 2, outlining the alignment between dimensions, indicators, and items measuring students' achievement motivation in mathematics learning.

Table 2. Blueprint of the Achievement Motivation Scale Instrument for Senior High School Students in Mathematics Learning

No	Dimension	Indicator	Code	Item	Total
1	Striving to excel	1) Striving to excel in mastering mathematical concepts	A.1.1	1, 2	2
		2) Striving to excel in completing mathematics assignments	A.1.2	11, 12	2
		3) Striving to excel in achieving mathematics test results	A.1.3	21, 22	2
2	Desire to obtain feedback	4) Desire to obtain feedback during the process of mastering mathematical concepts	A.2.1	3, 4	2
		5) Desire to obtain feedback from completing mathematics assignments	A.2.2	13, 14	2
		6) Desire to obtain feedback from mathematics test results	A.2.3	23, 24	2
3	Having personal responsibility	7) Studying mathematics on a scheduled basis	A.3.1	5, 6	2
		8) Attempting to rely on oneself in completing mathematics assignments	A.3.2	15, 16	2
		9) Attempting to rely on oneself in working on mathematics tests	A.3.3	25, 26	2
4	Doing things as best as possible	10) Attempting to master mathematical concepts as best as possible	A.4.1	7, 8	2
		11) Attempting to complete mathematics assignments as best as possible	A.4.2	17, 18	2
		12) Attempting to complete mathematics tests as best as possible	A.4.3	27, 28	2
5	Doing difficult tasks with satisfying results	13) Attempting to master difficult mathematical concepts	A.5.1	9, 10	2
		14) Attempting to complete difficult mathematics assignments	A.5.2	19, 20	2
		15) Attempting to complete difficult mathematics tests	A.5.3	29, 30	2
		Total			**30**

The blueprint consisted of five dimensions of achievement motivation, adapted from theoretical constructs previously identified in the analysis stage. Each dimension was operationalized into three indicators, with two items representing each indicator, resulting in a total of 30 items. The balanced distribution ensured that every aspect of the construct was captured proportionally, thereby supporting the content validity of the instrument (Patrick et al., 2011).

Content Validity Results

A question item is considered valid if the percentage of agreement between experts exceeds 50% (Julianto et al., 2025). Less appropriate question items are revised or eliminated based on expert input. The results of the content validation test showed that there were six questions that were declared valid because their agreement with the indicators was below 50%, namely, questions number 7, 8, 14, 16, 20, and 29, each of which received a score of 33%. Thus, out of 30 questions, there were 24 questions that were declared valid because they met the minimum agreement threshold of above 50%. The invalid questions were revised based on expert input regarding their inconsistency with the intended indicators. The revised questions, totaling six, were then included in a trial together with the validated questions and given to students at one of the high schools in Cirebon.

Usability Test Results

Before conducting field testing with students, this study first carried out a usability evaluation of the digital platform used to administer the achievement motivation scale instrument. The results of the usability evaluation are summarized in Table 3.

Table 3. Usability Evaluation Results of the Digital Achievement Motivation Scale Instrument

No	Evaluation Aspect	IT Experts (%)	Teachers (%)	Students (%)
1	Ease of access to Google Form	100	100	100
2	Clarity of instructions	66.7	66.7	33.3
3	Time efficiency when completing	100	100	100
4	Clarity of item statements	66.7	100	100
5	Increased motivation during digital completion	33.3	100	100
	Overall Average	**73.3**	**93.3**	**86.7**

The results of the usability test from three Information Technology (IT) experts showed an average value of 73%. This value meets the validity criteria because the level of agreement between experts exceeds the minimum threshold of 50%. However, there were findings that the Clarity of statement phrasing, relevance of items to the mathematical context, Appropriateness of Likert scale, and Digital usability potential aspects still need improvement, especially in the clarity of instructions and formulation of question item statements. Revisions were made based on expert input, including simplifying the instructions and improving the appearance of the Google Form to make it easier to use. Figure 1 is a display of the Achievement Motivation Scale Instrument (M-B Scale) in the form of a Google Form platform.

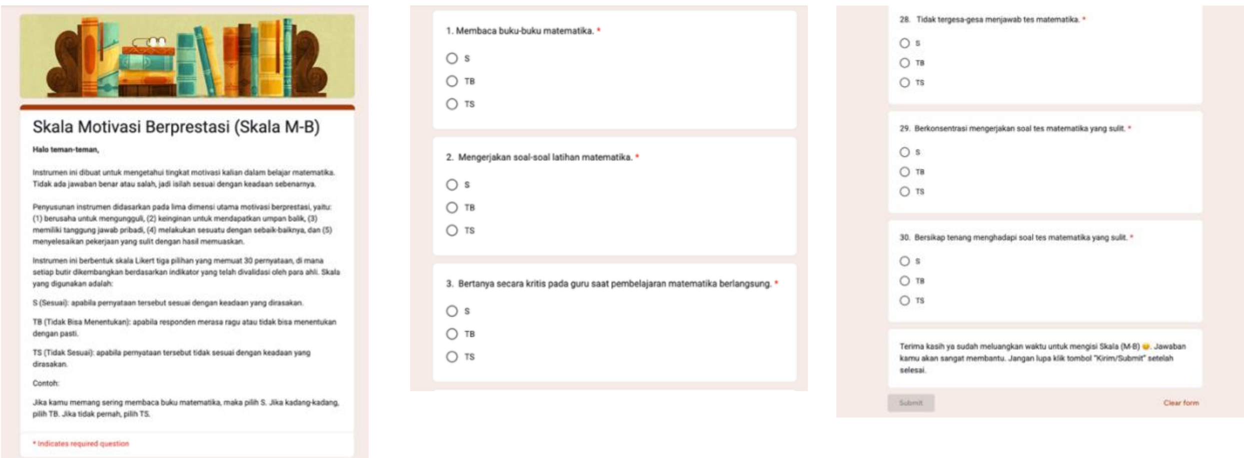

Figure 1. The Final Product Takes the Form of a Google Form (https://forms.gle/CM9tpXUU3EtSQbTC9)

After revisions were made based on usability evaluations by Information Technology experts, the next stage involved the involvement of actual users, teachers, and students to assess the feasibility and practicality of the achievement motivation scale instrument in the context of digital learning. The assessment used a binary assessment scale (1 = Yes, 0 = No) for five main aspects: ease of access to Google Form, clarity of instructions, time efficiency when filling in, clarity of question item statements, and the extent to which filling in the instrument digitally increases user motivation. This stage is important to ensure that the instrument is not only valid in terms of content but also user-friendly and appropriate for classroom applications.

The usability testing conducted by teachers and students indicates that the digital achievement motivation scale instrument is generally feasible for use in digital learning environments. Teachers rated the instrument as "highly feasible" with an average score of 93.3%, while students gave an average rating of 86.7%, categorizing it as "feasible to use." Both groups acknowledged the instrument's strengths in ease of access, time efficiency, clarity of item statements, and its ability to enhance motivation during digital completion.

However, one notable weakness identified by both groups was the clarity of the instructions. This aspect received the lowest score, which was 66.7% from teachers and only 33% from students, suggesting a need for revision. Based on this finding, improvements are recommended to simplify and clarify the instruction format. The revised instructions should use student-friendly language, avoid ambiguous phrasing, and include specific examples to guide users. Additionally, enhancing the visual presentation on mobile devices is suggested to further support ease of use.

Calculation Results of the Tabulation of Subject Response Data to Items

The tabulation of subject response data to the items begins with the first column of the table, which contains the frequency (*f*) for each response category. The total frequency, when summed, will equal the number of individuals who responded (*N*), which in this case is *N* = 57.

The second column represents the proportion (p), obtained by dividing each frequency by the total number of subjects. The third column is the p_i column, that denotes the cumulative proportion. The cumulative proportion is the proportion of a given response category added to the sum of proportions of all response categories to its left. For example, p_i for the "cannot determine" response on item number 1 is obtained by adding 0.11 (i.e., the p for the "does not reflect" category) to 0.49 (i.e., the p for the " cannot determine" category).

For example, the h, $Mindpoint_i$ for the response category "cannot determine" in item number 1, is calculated as 12(0.49)+0.11= 0.35. The distances between the response categories are expressed using z-score values. A z-score indicates the location of each response category along an interval-scaled continuum. The z-score for each $Mindpoint_i$ is obtained by referring to the standard normal distribution table.

Still on item 1, in the column with z = +1.620, we place the lowest score at zero, corresponding to the leftmost response category, namely 'does not reflect.' Figure 2 is the data of student responses for each statement item, along with the calculation results for each item, with the calculations assisted by Microsoft Excel:

	Number 1				Number 2		
	does not reflect	cannot determine	consistent with		does not reflect	cannot determine	consistent with
f	6,000	28,000	23,000	*f*	6,000	20,000	31,000
p	0,105	0,491	0,404	*p*	0,105	0,351	0,544
p_d	0,105	0,596	1,000	p_d	0,105	0,456	1,000
Midpointi	0,053	0,351	0,798	Midpointi	0,053	0,281	0,728
z	-1,62	-0,383	0,835	z	-1,62	-0,581	0,607
z+1.62	0	1,237	2,455	z+1.62	0	1,039	2,227

	Number 6				Number 7		
	does not reflect	cannot determine	consistent with		does not reflect	cannot determine	consistent with
f	8,000	15,000	34,000	*f*	5,000	14,000	38,000
p	0,14	0,263	0,596	*p*	0,088	0,246	0,667
p_d	0,14	0,404	1,000	p_d	0,088	0,333	1,000
Midpointi	0,07	0,272	0,702	Midpointi	0,044	0,211	0,667
z	-1,474	-0,607	0,529	z	-1,708	-0,805	0,431
z+1.47	0	0,867	2,004	z+1.62	0	0,903	2,138

Figure 2. Example of Subject Response Data Tabulation Calculation for an Item

Rounding in the last column of each table is performed as follows: if the value of z+... lies between 0.55 and 1.54, it is rounded to 1; if it lies between 1.55 and 2.54, it is rounded to 2. The rounding follows these rules for two decimal places:

a. If the digit to be rounded is greater than or equal to 5, it is rounded up (i.e., the digit to its left is increased by 1).
b. If the digit is less than 5, it is dropped and the digit to its left remains unchanged.

Based on these calculations, a combination of the three response scores should consistently be 0, 1, and 2. However, for items 8, 10, 18, and 24, the response combinations were 0, 1, and 3, indicating that these items must be discarded. After item reduction, the total number of valid items becomes 26.

Results of item discrimination power

The item discrimination power was assessed using the item-total correlation coefficient. This yielded a corrected item-total correlation coefficient, which provides a more accurate statistic for item discrimination. According to Azwar (2004), if the item-total correlation coefficient is calculated from a scale containing only a few items, there is a high likelihood that the coefficient will be overestimated due to overlap between the item score and the total scale score (Guilford, 1950). Table 4 shows the results of the item discrimination analysis and the category for each item.

Table 4. Results of the Correlation Coefficient Analysis between Item Scores and Total Scores

Item	Corrected Item-Total Correlation	Category	Item	Corrected Item-Total Correlation	Category
S1	0,463	moderate	**S16**	-0,001	very low
S2	0,562	moderate	**S17**	0,297	low
S3	0,405	moderate	**S19**	0,252	low
S4	0,48	moderate	**S20**	0,19	very low
S5	0,082	very low	**S21**	0,65	high
S6	0,209	low	**S22**	0,652	high
S7	0,34	low	**S23**	0,306	low
S9	0,334	low	**S25**	0,42	moderate
S11	0,293	low	**S26**	0,335	low
S12	0,349	low	**S27**	0,348	low
S13	0,2	low	**S28**	0,185	very low
S14	0,145	very low	**S29**	0,445	moderate
S15	-0,015	very low	**S30**	0,425	moderate

As a criterion for item selection based on item-total correlation, a threshold of riX ≥ 0.300 is typically used. Any item reaching a minimum correlation coefficient of 0.3 is considered to have satisfactory discrimination power (Azwar, 2004). Out of 26 items, 12 were not selected due to their correlation coefficients being ≤ 0.300, namely items number 5, 6, 11, 13, 14, 15, 16, 17, 19, 20, 23, and 28. The remaining 14 items will be further analyzed for validity and reliability. Some indicators lost their corresponding items; ideally, these items should be revised or replaced entirely with new items and retested in a field test, so that no indicators are missing within a given dimension. However, due to time constraints that prevent a retest, the analysis will proceed using the remaining items.

Results of the Construct Validation Test

Construct validity testing was conducted using factor analysis. In this case, the aim was to determine how many factors the statement items would group into. To obtain this information, an exploratory analysis technique was used. Exploratory factor analysis (EFA) allows the test items to naturally group themselves through extraction based on the construct factors from which the items originate (Julianto et al., 2025).

This study employed exploratory factor analysis (EFA) because it enables the exploration of the underlying factor structure of the items in the instrument, especially when the structure is not yet known (Julianto et al., 2025). EFA also provides flexibility in the natural grouping of items based on relevant dimensions without prior assumptions and allows for the identification of new dimensions emerging from the data, offering deeper insight into students' achievement motivation. The following are the results of the construct validity testing analysis (see Fig. 3).

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.713
Bartlett's Test of Sphericity	Approx. Chi-Square	431.594
	df	91
	Sig.	.000

Figure 3. Results of KMO and Bartlett's Tests

Based on the results of the factor feasibility analysis above, the KMO value was obtained at 0.713 > 0.05 and with a Bertlett's sig. Value of 0.000 < 0.05, this means that this instrument is said to be valid (see Fig. 4).

		S1	S2	S3	S4	S7	S9	S12	S21	S22	S23	S25	S26	S29	S30
Anti-image	S1	.715a	-.576	.041	-.053	.130	-.039	-.149	-.237	.196	-.144	.005	-.243	-.138	.292
Correlation	S2	-.576	.791a	-.143	-.135	-.202	-.059	-.124	.074	-.032	-.055	-.268	.016	.088	-.014
	S3	.041	-.143	.746a	-.439	-.041	.238	-.082	-.153	.113	-.027	.195	-.282	-.084	.021
	S4	-.053	-.135	-.439	.767a	-.047	.079	.279	-.216	.039	.029	.159	.202	-.143	-.013
	S7	.130	-.202	-.041	-.047	.772a	-.236	-.229	-.152	.052	-.048	-.130	.114	-.074	.278
	S9	-.039	-.059	.238	.079	-.236	.626a	-.001	-.202	.154	-.131	.299	-.298	-.160	-.061
	S12	-.149	-.124	-.082	.279	-.229	-.001	.711a	-.094	.029	.188	.163	.146	-.119	-.204
	S21	-.237	.074	-.153	-.216	-.152	-.202	-.094	.715a	-.875	-.054	.005	.258	.099	-.184
	S22	.196	-.032	.113	.039	.052	.154	.029	-.875	.712a	-.095	-.076	-.319	.042	-.008
	S23	-.144	-.055	-.027	.029	-.048	-.131	.188	-.054	-.095	.859a	-.097	.166	.125	-.044
	S25	.005	-.268	.195	.159	-.130	.299	.163	.005	-.076	-.097	.681a	-.394	-.494	.026
	S26	-.243	.016	-.282	.202	.114	-.298	.146	.258	-.319	.166	-.394	.567a	.193	-.187
	S29	-.138	.088	-.084	-.143	-.074	-.160	-.119	.099	.042	.125	-.494	.193	.654a	-.664
	S30	.292	-.014	.021	-.013	.278	-.061	-.204	-.184	-.008	-.044	.026	-.187	-.664	.696a

a. Measures of Sampling Adequacy(MSA)

Figure 4. Anti-Image Matrices

Based on the anti-image matrix table in Figure 4, we can see that the MSA of the 14 items is valid, because the MSA value of all items is more than 0.5.

Component Matrix[a]					
	Component				
	1	2	3	4	5
S1	.640	-.229	.532	-.058	-.222
S2	.708	-.188	.469	-.011	-.287
S3	.564	-.359	-.298	-.126	-.422
S4	.568	-.465	-.411	-.081	-.251
S7	.517	-.325	.226	.435	.060
S9	.428	.086	.234	.345	.551
S12	.447	.173	.015	.688	-.174
S21	.832	-.204	-.303	-.041	.249
S22	.785	-.096	-.298	-.173	.310
S23	.471	-.371	.094	-.227	.430
S25	.556	.561	.245	-.276	-.114
S26	.452	.424	.312	-.466	.068
S29	.564	.646	-.177	.144	-.182
S30	.572	.615	-.404	.072	.034

Extraction Method: Principal Component Analysis.
a. 5 components extracted.

Figure 5. Results of Component Matrix Analysis

The values in the Component Matrix table (see Fig. 5) represent the correlations between each item and the respective factors formed. To determine which factor an item belongs to, a rotation of the component matrix was performed. The highest loading value of each item corresponds to its designated factor group.

a. Items 25 and 26 are grouped into Factor 1. I labeled Factor 1 as Self-Reliance in Taking Math Tests.
b. Items 3 and 4 are grouped into Factor 2. I labeled Factor 2 as Desire to Receive Feedback During Concept Mastery in Mathematics.
c. Items 9, 21, and 22 are grouped into Factor 3. I labeled Factor 3 as Undertaking Challenging Tasks to Excel in Mathematical Concepts and Test Results.
d. Items 1 and 2 are grouped into Factor 4. I labeled Factor 4 as Striving to Excel in Concept Mastery.
e. Items 7, 12, 29, and 30 are grouped into Factor 5. I labeled Factor 5 as Making the Best Effort in Learning, Assignments, and Mathematics Tests.

The factor analysis in this calculation is intended for grouping, not for selecting. Therefore, the items on this achievement motivation scale are grouped into five factors, namely: relying on oneself to complete mathematics tests, the desire to receive feedback during the process of mastering mathematical concepts, engaging in challenging tasks to excel in mathematical concepts and test results, and striving to do one's best in mathematics learning, assignments, and tests. This achievement motivation scale is considered a unidimensional scale because it consists of several components or factors. If the scale were multidimensional, it would consist of only one component or factor.

Reliability Test Results

Figure 6 displays the output of the reliability test conducted to examine the internal consistency of the achievement motivation instrument.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.841	.839	14

Figure 6. Results of Reliability Test Analysis

The Cronbach's Alpha value for the entire achievement motivation scale instrument is 0.841 (see Fig. 6). Since the calculated r-value > r-table, or 0.841 > 0.266, it can be concluded that the instrument is significantly reliable.

Score Interpretation

The purpose of level categorization is to place individuals into tiered groups along a continuum based on the attribute being measured (Azwar, 2004). The level categories in this scale are low, medium, and high. The achievement motivation scale for high school students in mathematics learning consists of 14 items that are considered valid and reliable, with each item scored as follows: 0 for "Not Appropriate," 1 for "Cannot Determine," and 2 for "Appropriate."

The minimum-maximum range is 14 × 0 = 0 to 14 × 2 = 28, resulting in a total spread of 28 – 0 = 28. Thus, each standard deviation unit is valued at σ = 28/6 = 4,67 (divided by 6 because a normal distribution is divided into 6 standard deviation units), and the theoretical mean is μ = 14 × 1 = 14 (where 1 is derived from the average score, i.e., (0+2)/2). If it is desired to classify subjects into 3 diagnostic categories of achievement motivation, then the six standard deviation units are divided into three parts, as follows. Given that σ = 4,67. The achievement motivation score categories are presented in Table 5.

Table 5. Categorization Formula

Score Range (X)	Motivation Level
$X < [14 - 1{,}0(4{,}67)]$	Low
$[14 - 1{,}0(4{,}67)] \leq X < [14 + 1{,}0(4{,}67)]$	Medium
$[14 + 1{,}0(4{,}67)] \leq X$	High

The categories are presented in Table 6.

Table 6. Concrete Results of Score Categorization

Score Range (X)	Motivation Level
X < 9,33	Low
9,33 ≤ X < 18,67	Medium
X ≥ 18,67	High

The findings of this study demonstrate that achievement motivation in mathematics learning can be assessed reliably through a digitally administered instrument. The high level of internal consistency and the acceptable psychometric indicators provide empirical support for the feasibility of digital questionnaire-based data collection, particularly in Indonesian high school settings. This result aligns with recent studies suggesting that digital platforms can improve measurement accessibility, reduce administrative burden, and increase student engagement when appropriately designed (Badanbekkyzy et al., 2025; Rosário & Dias, 2022).

The exploratory factor analysis revealed a four-factor structure that differs slightly from the original conceptual dimensions, even though all retained factors remained conceptually grounded in classic achievement motivation theory. The four-factor structure, namely Perseverance in Learning, Diligence in Study, Initiative in Work, and Tenacity in Solving Problems, aligned with McClelland (1961) classic achievement motivation theory and subsequent models emphasizing effort, persistence, and initiative. While the instrument was initially constructed across five theoretical dimensions, empirical testing showed that several dimensions merge into broader but coherent constructs. For example, indicators related to perseverance, hard work, and sustaining effort across tasks clustered strongly, suggesting that students perceive these expressions of motivation holistically rather than as distinctly separate traits. This is consistent with previous findings that motivational constructs manifest differently across cultural and learning contexts (Ulum, 2025; Wang et al., 2022; Zhang et al., 2025).

Compared to previous studies that developed general motivation scales (Hossein-Mohand & Hossein-Mohand, 2023), this study highlights the domain-specific nature of mathematics motivation, where persistence and problem-solving emerge as particularly salient dimensions. Surprisingly, some items originally designed to capture "initiative" were dropped during factor analysis, suggesting that Indonesian high school students may conceptualize initiative differently in the context of mathematics tasks.

A key interpretation emerging from the usability findings is the contrast between teacher and student perceptions. Teachers rated usability highly, particularly in terms of clarity and ease of navigation, yet students identified greater difficulties, especially regarding wording and interface presentation. This discrepancy reflects the need to design digital learning instruments with student-centered language and device-specific adaptability, which echoes findings from recent educational technology research emphasizing the importance of user experience in learner-facing systems (Tawfik et al., 2024). Addressing these concerns will likely improve data quality and foster greater student willingness to engage with digital assessment tools.

Taken together, these results suggest that digital psychometric tools hold strong potential for supporting formative evaluation and strengthening student profiling in mathematics classrooms. The validated instrument may be used to diagnose learning support needs, identify students requiring motivational intervention, or evaluate the impact of instructional strategies aimed at fostering persistence and productive study habits. Continued refinement and wider field testing could further enhance precision and applicability across school settings.

LIMITATIONS

This study has several limitations that should be acknowledged. First, the field test involved a relatively small and context-specific sample consisting of grade X high school students from a single region in Indonesia. As a result, the findings may not fully represent students from different grade levels, school types, or cultural contexts, and therefore limit the generalizability of the results. In addition, the instrument was developed specifically for mathematics learning and may not be directly applicable to other subjects without further adaptation and validation.

Second, the study relied solely on self-report data collected through a digital platform, which may be influenced by students' interpretation of items, digital literacy, and access to devices. The differences observed between teacher and student usability ratings also suggest that the interface design and instructional clarity may affect how students engage with the instrument. Future studies should involve larger and more diverse participants, integrate confirmatory factor analysis, and consider behavioral indicators or performance data to further strengthen the construct and enhance the practical utility of the digital instrument.

CONCLUSION

This study aims to develop an achievement motivation scale instrument for high school students in mathematics learning, delivered through a digital questionnaire platform (micro testing). The development seeks to produce a valid, reliable, and practical measurement tool that can effectively identify students' achievement motivation levels based on five theoretical dimensions, and is user-friendly for students, teachers, and other stakeholders in a technology-based learning context. A total of 30 items were constructed based on five dimensions of achievement motivation: striving for excellence, desire to receive feedback, personal responsibility, best effort, and completing difficult tasks. Content validation was conducted by three experts, resulting in 24 valid items (86.7%) and six items that required revision. Usability evaluation by three information technology experts, three teachers, and three students showed positive results, with average scores of 73%, 93.3%, and 86.7%, respectively, indicating that the instrument was user-friendly and well-accepted. Field testing with 57 students revealed that 14 items met the discrimination index threshold (r ≥ 0.30). Exploratory Factor Analysis (EFA) showed factor loadings ranging from 0.40 to 0.85, supporting the construct validity of the instrument. Reliability testing using Cronbach's Alpha yielded a value of 0.89, indicating a high level of internal consistency. Therefore, the 14 items are considered valid, reliable, and feasible for measuring students' achievement motivation in mathematics learning through a digital platform.

This study is still limited to a small sample size, so it is recommended that a larger-scale trial be conducted with a more diverse student population in order to obtain more generalizable results. In addition, it is important to use Confirmatory Factor Analysis (CFA) to re-test the factor structure obtained from EFA. Future research could also use a longitudinal design to observe changes in student achievement motivation over a certain period of time, as well as integrate this instrument with adaptive digital learning systems to assess its impact on learning outcomes. Furthermore, this instrument could also be tested in subjects other than mathematics to determine its broader applicability.

ACKNOWLEDGMENT

The author would like to express sincere gratitude to Nahdlatul Ulama University Cirebon for its invaluable support and contribution throughout the research process. The facilities, guidance, and encouragement provided by the institution have been instrumental in the completion of this study. Without such support, this research would not have been possible.

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