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Psychometric Validity Analysis of Logical–Mathematical Intelligence

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ABSTRACT

This study is a validation and instrument-development research whose primary goal is to examine and ensure the psychometric quality of a Logical–Mathematical Intelligence (LMI) questionnaire for Senior High School students. LMI, as a fundamental aspect of scientific reasoning, requires a well-established measurement tool. The adapted instrument consists of 24 items using a five-point Likert scale and was constructed based on Gardner's five core LMI dimensions (numerical ability, logical reasoning, problem solving, pattern recognition, and deductive/inductive thinking). Data were collected online from 317 high school students through convenience sampling. Analysis was performed using the Rasch Model (Winsteps 3.73). The results indicate that the instrument demonstrates adequate unidimensionality (raw variance explained 33.3%) and excellent reliability (Cronbach's Alpha 0.89; Item Reliability 0.96). All items were found to be fit and functioning properly, with strong discriminative power (Item Separation 4.98), indicating that the instrument can classify item difficulty into seven distinct levels. These findings explicitly confirm that the adapted LMI questionnaire meets international psychometric standards and is valid for mapping the logical–mathematical reasoning abilities of high school students.

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Introduction

Logical–Mathematical Intelligence (LMI) is one of the nine types of multiple intelligences introduced by Gardner (2011). This intelligence reflects an individual's core ability to perform calculations, engage in logical reasoning, and solve problems systematically (Kemala Sari et al., 2020). LMI is also defined as the capacity to understand numbers, concepts, shapes, and patterns in order to solve problems in daily life through reasoning (Nur et al., 2018). In educational literature, the terms *Logical–Mathematical Intelligence*, *Logical–Mathematical Ability*, and *Mathematical Logical Intelligence* are often used interchangeably, as they refer to a similar construct (Dwita et al., 2022; Widiastuti et al., 2023). LMI is essential for the development of abilities involving pattern recognition, sequencing, mathematical problem solving, and strategic thinking in daily contexts (Ansari et al., 2024). At its core, this intelligence encompasses the capacity to reason, identify patterns, perform abstractions, and recognize causal relationships. Beyond its relevance in everyday life, LMI is a fundamental component of students' cognitive development and plays a crucial role in mathematics learning. Gardner (2011) defines LMI as the ability to work with numbers and computations, as well as to manipulate patterns and logical–scientific thinking. This intelligence is vital in mathematical problem solving, as it includes the ability to think inductively and deductively, understand and analyze patterns, and construct solutions (Gardner, 2011). More specifically, LMI encompasses an individual's ability to understand and use logic, symbols, numerical information, and numerical operations.

Logical–Mathematical Intelligence (LMI) encompasses an individual's ability to understand numerical information and engage in accurate reasoning, enabling a person to be more sensitive to causes and potential solutions to problems through logical reflection (Rofiqotul Musyarrofah & Rahmat, 2025). The fact that many students are still unable to employ deductive reasoning to solve contextual problems indicates the need to further develop logical–mathematical intelligence (Hidayatulloh et al., 2024). Moreover, the ability to work with numbers, reasoning, and relational thinking is also a key representation of this intelligence (Kandeel, 2016; Nindriyati, 2017). Logical thinking involves the capacity to reason rationally using one's logical capabilities (Nisa et al., 2024). Students with higher levels of LMI tend to more easily understand, analyze, and solve problems accurately (Dwita et al., 2022), as they are able to interpret tasks, predict outcomes, solve problems, and draw conclusions (Yunisca & Nasution, 2023). Characteristics of students with strong logical–mathematical intelligence are supported by empirical evidence showing proficiency in mathematical computation, logical thinking during problem solving, sensitivity to causal relationships and patterns, as well as skill in both deductive and inductive reasoning (Asmal, 2020; Islamy & Indrawati, 2024; Sihab, 2021; Zulkarnain & Nurbiati, 2019).

Given the crucial role of logical–mathematical intelligence in assessing students' potential and scientific reasoning abilities, it is essential to ensure that the instruments used to measure this construct possess strong psychometric quality. An assessment instrument must demonstrate valid and reliable evidence to confirm that it accurately measures the intended construct of logical–mathematical intelligence.

Building on this urgency, the present study focuses on the Psychometric Validity Analysis of a Logical–Mathematical Intelligence questionnaire consisting of 24 items administered to 317 high school students. Specifically, the research aims to answer the following questions:

1. What is the level of item validity in the Logical–Mathematical Intelligence questionnaire based on Rasch Model analysis?
2. What is the level of reliability of the questionnaire according to the Rasch Model?
3. How are the item difficulty levels and respondent ability (person ability) distributed within the questionnaire?

To address these questions, the study employs the Rasch Model using Winsteps 3.73 as the primary analytical framework..

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
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Method

Types of Research

This study adopts a quantitative approach using an Instrument Development and Validation Study design. The purpose of this research is to evaluate the psychometric quality of the Logical–Mathematical Intelligence questionnaire through Rasch Model analysis. This design is more appropriate than a purely descriptive study because the primary focus is on the technical characteristics of the instrument, specifically examining its validity and reliability as well as assessing the functioning of each item. The study employs a descriptive method with logical–mathematical intelligence as the variable being measured.

Population and Sample

The population of this study consists of senior high school (SMA) students in Indonesia. The sample includes 317 students from various schools, representing diverse levels of intelligence and academic backgrounds. The sample was selected using a convenience sampling technique, in which the questionnaire was distributed online via Google Forms over a two-week period. This approach was chosen due to limitations in time and resources. The respondents were active SMA students who regularly engage in academic activities, making them relevant to the construct of Logical–Mathematical Intelligence. Although individual intelligence levels were assumed to vary, the data collected were used to map the distribution of respondent ability (person ability) within the Rasch Model framework, rather than to compare specific intelligence groups.

Instruments

Data were collected using a Logical–Mathematical Intelligence questionnaire consisting of 24 items measured on a five-point Likert scale. This instrument is an adapted version previously used by other researchers, with items constructed based on the five core aspects of logical–mathematical intelligence as defined in Gardner (2011) framework. These five aspects include: (1) the ability to perform mathematical computations; (2) logical reasoning skills; (3) problem-solving ability; (4) the capacity to recognize logical patterns and relationships; and (5) deductive and inductive thinking. Since this instrument is an adapted measure that has not undergone expert content validation by the current research team, this study considers it necessary to conduct further empirical psychometric validation using the Rasch Model to provide evidence of item quality and functioning within the population of senior high school students. Table 1 presents the instrument blueprint based on Gardner's dimensions:

Table 1. Blueprint of the Logical–Mathematical Intelligence Psychometric Instrument

Aspect	Item of Numbers
Mathematical computation ability	1, 19, 24
Logical reasoning ability	7, 3, 6, 11, 13, 15, 21, 22
Problem-solving ability	5, 2, 9, 10, 17, 20
Pattern recognition and logical relational ability	4, 8, 14, 23
Deductive and inductive thinking	12, 16, 18

Data Collection

The data collection process was carried out in several systematic stages. First, the 24-item Logical-Mathematical Intelligence (LMI) questionnaire was adapted and digitized into a Google Forms format to facilitate wide-reaching online distribution. Second, the researchers coordinated with several senior high schools to identify potential respondents. Third, the questionnaire was distributed via social media platforms and direct links to student groups over a two-week period. Participation was voluntary, and students were informed about the purpose of the study and the confidentiality of their responses before proceeding. After the data collection period, the raw responses from 317 students were exported to a spreadsheet. Finally, the valid data were converted into a PRN file format to be processed and analyzed using Winsteps software version 3.73.

Data Analysis

Data were analyzed using the Rasch Model (Single-Parameter Item Measurement Model) with the assistance of Winsteps software version 3.73. The Rasch Model was chosen due to its ability to simultaneously assess item validity and reliability, as well as to map respondent ability and item difficulty on a common scale.

The analytical parameters employed in this study include several essential aspects of psychometric validation:

1. Construct Validity (Unidimensionality Test):
   Assessed using Principal Component Analysis of Residuals (PCAR) to ensure that the instrument measures a single latent dimension (Logical–Mathematical Intelligence).
2. Item Fit Statistics:
   Evaluated through OUTFIT and INFIT Mean Square (MNSQ) indices and Z-Standard (ZSTD) values. This analysis is crucial for identifying items that do not function according to the Rasch Model, providing evidence for item-level validity.
3. Reliability and Separation Index:
   - Item and Person Reliability: Measured using the Item Reliability Index and Person Reliability Index to assess the consistency of measurement results.
   - Separation Index: Measured using the Person Separation Index and Item Separation Index to determine the instrument's ability to distinguish different levels of respondent ability and item difficulty.
4. Differential Item Functioning (DIF):
   Conducted to identify items that may function differently across respondent subgroups (e.g., gender) despite having the same underlying ability level.
5. Construct Map (Wright Map):
   Used to visualize the relationship between the distribution of item difficulty levels and respondent ability levels.

Data analysis was conducted using the Rasch Model, a method designed to measure students' logical–mathematical intelligence, with the assistance of Winsteps version 3.73. Reliability in the Rasch Model is assessed through two components: item reliability and person reliability. The item reliability index evaluates whether the same items produce consistent responses across different respondents. Meanwhile, the person reliability index assesses whether variations in respondents affect the consistency of measurement for each construct.

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v5i4.2596 Volume 5, No 4, October - December 2025, pp. 1720 – 1730

Research Findings

Unidimensionality

Research instruments play a crucial role in any study, as the accuracy of the instrument directly affects the validity of the data obtained. Data validity, in turn, determines the overall quality of the research findings. To ensure that the data collected are accurate, the research instrument must be valid and appropriate. In this context, validity and reliability testing are essential steps in producing a sound measurement tool. According to Ghozali (2009), a validity test is used to assess whether a questionnaire is legitimate and capable of measuring what it is intended to measure. A questionnaire is considered valid if its items successfully capture the construct being measured. The psychometric validity of the Logical–Mathematical Intelligence instrument, consisting of 24 items administered to 317 high school students, was analyzed using the Rasch Model.

The unidimensionality analysis aims to determine whether the instrument measures a single underlying construct. This analysis was conducted using the output from Table 2 of the Winsteps version 3.73 software, focusing on the raw variance explained by the measures and the unexplained variance in the first through fifth contrasts. An instrument is considered unidimensional when the raw variance explained by the measures reaches at least 20%. Generally, the interpretation criteria are as follows: acceptable if between 20–40%, good if between 40–60%, and excellent if above 60%. Additionally, the unexplained variance in the residuals for the first through fifth contrasts should each be below 15%.

Table 2. Results of the Unidimensionality Analysis

Table of RAW RESIDUAL variance (in Eigenvalue units)

		-- Empirical --			Modeled
Total raw variance in observations	=	36.0	100.0%		100.0%
Raw variance explained by measures	=	12.0	33.3%		33.8%
Raw variance explained by persons	=	3.6	10.1%		10.3%
Raw Variance explained by items	=	8.3	23.2%		23.5%
Raw unexplained variance (total)	=	24.0	66.7%	100.0%	66.2%
Unexplned variance in 1st contrast	=	3.0	8.4%	12.6%	
Unexplned variance in 2nd contrast	=	2.5	6.9%	10.3%	
Unexplned variance in 3rd contrast	=	2.2	6.2%	9.3%	
Unexplned variance in 4th contrast	=	1.4	4.0%	6.0%	
Unexplned variance in 5th contrast	=	1.3	3.5%	5.2%	

Based on Table 2, the raw variance explained by the measures reached 33.3%, which falls within the acceptable category. Furthermore, the unexplained variance in the 1st contrast was 8.4%, in the 2nd contrast 6.9%, in the 3rd contrast 6.2%, in the 4th contrast 4.0%, and in the 5th contrast 3.5%. All values are below the 15% threshold, indicating that the instrument meets the unidimensionality criteria and is appropriate for assessing logical–mathematical intelligence.

Table 3. Summary Statistic Person

SUMMARY OF 317 MEASURED PERSON

	TOTAL SCORE	COUNT	MEASURE	MODEL ERROR	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	78.6	24.0	.249	.202	1.04	-.1	1.03	-.1
S.D.	15.9	.0	.628	.026	.52	1.8	.50	1.8
MAX.	110.0	24.0	1.814	.317	3.31	5.3	3.11	5.5
MIN.	49.0	24.0	-.870	.184	.10	-6.5	.12	-6.3

REAL RMSE .228 TRUE SD .585 SEPARATION 2.57 PERSON RELIABILITY .87
MODEL RMSE .204 TRUE SD .594 SEPARATION 2.91 PERSON RELIABILITY .89
S.E. OF PERSON MEAN = .035

PERSON RAW SCORE-TO-MEASURE CORRELATION = .99
CRONBACH ALPHA (KR-20) PERSON RAW SCORE "TEST" RELIABILITY = .89

Table 4. Summary Statistic Item

SUMMARY OF 24 MEASURED ITEM

	TOTAL SCORE	COUNT	MEASURE	MODEL ERROR	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	1037.7	317.0	.000	.055	1.01	-.2	1.03	.1
S.D.	97.1	.0	.296	.002	.30	4.1	.29	3.9
MAX.	1288.0	317.0	.566	.063	1.70	8.0	1.64	7.5
MIN.	845.0	317.0	-.816	.054	.59	-6.9	.60	-6.5

REAL RMSE .058 TRUE SD .290 SEPARATION 4.98 ITEM RELIABILITY .96
MODEL RMSE .055 TRUE SD .291 SEPARATION 5.31 ITEM RELIABILITY .97
S.E. OF ITEM MEAN = .062

UMEAN=.0000 USCALE=1.0000
ITEM RAW SCORE-TO-MEASURE CORRELATION = -1.00
7608 DATA POINTS. LOG-LIKELIHOOD CHI-SQUARE: 20722.90 with 7265 d.f. p=.0000
Global Root-Mean-Square Residual (excluding extreme scores): 1.0324

The person measure analysis provides an overview of the average scores obtained by respondents on the logical–mathematical intelligence test. When the mean person value is higher than the mean item value—where the item mean is anchored at 0.00 logits—this indicates that the respondents' overall ability exceeds the difficulty level of the items in the instrument. Reliability was assessed using Cronbach's Alpha, which is categorized into four levels: excellent (0.80 to 1.00), good (0.70 to 0.80), adequate (0.60 to 0.70), and poor (0.00 to 0.60) (Bond, Yan, & Heene, 2015). In this analysis, the Cronbach's Alpha value representing the overall interaction between persons and items was 0.89, which falls into the excellent category. The person reliability index was 0.87, indicating a good level of response consistency. Meanwhile, the item reliability index reached 0.96, suggesting that the quality of the items in the instrument is outstanding.

Based on the Person Table 3, the mean INFIT MNSQ value was 1.04, while the mean OUTFIT MNSQ value was 1.03. From the Item Table 3, the mean INFIT MNSQ was 1.01 and the mean OUTFIT MNSQ was 1.03. Values approaching 1 indicate better measurement quality, indicating that both person and item averages obtained in this study are close to the ideal range. Furthermore, regarding the INFIT ZSTD, the mean value for persons was −0.1, and the OUTFIT ZSTD was also −0.1. For items, the INFIT ZSTD reached −0.2, while the OUTFIT ZSTD was 0.1. The ideal ZSTD value is 0; thus, the closer the values are to zero, the better the quality. Accordingly, it can be concluded that both person and item quality are well maintained.

Finally, the separation indices for both persons and items were examined. Person separation reflects how well the items in the logical–mathematical intelligence instrument are distributed across the range of respondent abilities. The higher the person separation value, the

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v5i4.2596 Volume 5, No 4, October - December 2025, pp. 1720 – 1730

better the instrument is at capturing individuals across the full spectrum of ability, from the lowest to the highest. Conversely, item separation describes how well the sample is distributed along the linear interval scale. A higher item separation value indicates stronger measurement precision.

Table 3 shows that the person separation value is 2.57, while Table 4 indicates that the item separation value reaches 4.98. To calculate separation strata, the formula $H = ((4 \text{ x separation}) + 1) / 3$ is used. Based on this formula, the person separation strata value is 3.76, rounded to 4, whereas the item separation strata value is 6.97, rounded to 7. Higher separation values indicate stronger measurement quality for both persons and items. These findings demonstrate that the respondents in this study possess a wide range of abilities that can be grouped into three distinct categories, while the items vary in difficulty across seven groups, from the easiest to the most difficult.

Item Analysis

Item analysis consists of two key components: the item difficulty level (item measure) and the item fit statistics. Both aspects are explained in more detail below.

Item Difficulty Level

The difficulty level of each item can be evaluated using Table 5, which displays the ordered item measures generated by the Winsteps application. From this table, the standard deviation value obtained is 0.296. By combining this value with the logit mean, item difficulty can be categorized into several levels. These categories include: very difficult (greater than +1 SD), difficult (between 0.0 logits and +1 SD), easy (between 0.0 logits and –1 SD), and very easy (less than –1 SD). Accordingly, the cutoff score for the very difficult category is defined as values greater than 0.296, while the difficult category ranges from 0.0 to 0.296. For the easy category, values fall between 0.0 and –0.296, and the very easy category includes values below –0.296. Based on the logit values for each item in Table 5, the items can be grouped from the most difficult to the easiest. Three items fall into the *very difficult* category: items 18, 21, and 10. Nine items are categorized as *difficult*, namely items 20, 14, 8, 19, 1, 9, 12, 11, and 2. Additionally, seven items are classified as *easy*: items 13, 6, 7, 15, 4, 22, and 5. Finally, three items are identified as *very easy*, namely items 3, 16, and 17. The results of the item difficulty analysis are presented in Table 5.

Tabel 5. Item Fit Statistics

ENTRY	TOTAL	TOTAL		MODEL	INFIT		OUTFIT			PT-MEASURE		EXACT MATCH		
NUMBER	SCORE	COUNT	MEASURE	S.E.	MNSQ	ZSTD	MNSQ	ZSTD		CORR.	EXP.	OBS%	EXP%	ITEM
3	1146	317	-.320	.056	1.70	8.0	1.51	5.7	A	.53	.51	24.3	36.4	Q3
13	1043	317	-.008	.054	1.45	5.6	1.64	7.5	B	.49	.54	24.6	34.6	Q13
8	1001	317	.114	.054	1.36	4.7	1.42	5.3	C	.51	.55	25.9	33.7	Q8
9	1012	317	.082	.054	1.31	4.1	1.40	5.0	D	.51	.55	26.5	34.0	Q9
16	1175	317	-.413	.057	1.38	4.6	1.31	3.6	E	.50	.50	30.3	36.4	Q16
18	845	317	.566	.054	1.29	3.8	1.31	4.0	F	.56	.57	22.7	32.1	Q18
2	1040	317	.001	.054	1.19	2.6	1.26	3.3	G	.51	.54	26.8	34.6	Q2
6	1046	317	-.017	.054	1.17	2.3	1.18	2.3	H	.58	.54	29.0	34.7	Q6
22	1087	317	-.139	.055	1.13	1.7	1.11	1.4	I	.52	.53	38.2	35.8	Q22
21	875	317	.478	.054	1.06	.9	1.10	1.4	J	.54	.57	24.9	32.1	Q21
7	1048	317	-.023	.054	1.08	1.1	1.09	1.3	K	.50	.54	33.1	34.7	Q7
17	1183	317	-.439	.057	1.01	.1	.99	-.1	L	.50	.49	44.5	37.4	Q17
24	1288	317	-.816	.063	.99	-.1	.97	-.3	l	.50	.44	48.6	41.9	Q24
19	1002	317	.111	.054	.92	-1.1	.96	-.6	k	.50	.55	38.5	33.7	Q19
20	989	317	.149	.054	.87	-1.9	.89	-1.6	j	.64	.55	39.1	33.3	Q20
10	887	317	.443	.054	.82	-2.7	.83	-2.5	i	.63	.57	33.4	32.1	Q10
12	1012	317	.082	.054	.80	-3.0	.82	-2.6	h	.53	.55	42.3	34.0	Q12
14	999	317	.120	.054	.77	-3.5	.82	-2.7	g	.52	.55	44.2	33.7	Q14
23	967	317	.212	.054	.79	-3.2	.79	-3.1	f	.65	.56	41.6	32.9	Q23
15	1052	317	-.035	.054	.73	-4.2	.76	-3.5	e	.53	.54	43.2	34.7	Q15
5	1125	317	-.254	.056	.62	-6.1	.68	-4.8	d	.52	.52	52.1	36.3	Q5
11	1017	317	.068	.054	.63	-6.2	.67	-5.3	c	.56	.55	48.6	34.0	Q11
4	1062	317	-.064	.054	.62	-6.2	.65	-5.4	b	.54	.54	46.4	35.3	Q4
1	1004	317	.105	.054	.59	-6.9	.60	-6.5	a	.63	.55	47.0	33.7	Q1
MEAN	1037.7	317.0	.000	.055	1.01	-.2	1.03	.1				36.5	34.7	
S.D.	97.1	.0	.296	.002	.30	4.1	.29	3.9				9.2	2.0	

Table 5 indicates that, based on the first criterion, two items—items 3 and 13—are classified as misfit. Meanwhile, according to the second criterion, seven items meet the acceptable fit requirements, namely items 22, 21, 7, 17, 24, 19, and 20. Based on the third criterion, all items fall within the fit category. Overall, it can be concluded that all items in the logical–mathematical intelligence instrument are considered fit, indicating that they function properly within the measurement model.

Discussion

The results of this psychometric analysis provide strong empirical evidence for the quality of the adapted Logical-Mathematical Intelligence (LMI) instrument. The primary finding regarding unidimensionality showed a raw variance explained by measures of 33.3%, confirming that the 24 items primarily measure a single latent trait, which aligns with Gardner's (2011) theoretical framework. Distinct from many previous studies on Logical-Mathematical Intelligence that predominantly rely on Classical Test Theory (CTT), this research employs the Rasch Model to provide a more objective and granular calibration of the instrument's psychometric properties. While CTT-based studies typically only report a general reliability coefficient (Alpha Cronbach), this study utilizes the Separation Index to demonstrate that the instrument is capable of distinguishing item difficulty into seven distinct levels (Item Strata = 6.97). This level of precision is a significant advancement, as it allows for a more detailed mapping of logical reasoning abilities moving beyond a simple "pass/fail" or "high/low" categorization to a more nuanced hierarchy of logical tasks.

The high reliability scores (Cronbach's Alpha = 0.89 and Item Reliability = 0.96) further indicate that the item hierarchy remains stable across different student populations. The item difficulty analysis revealed that items involving complex deductive thinking (Items 18, 21, and 10) were the most challenging. This finding supports the work of Hidayatulloh et al. (2024), which noted that high school students often face difficulties when transitioning from basic computation to abstract logical reflection. By providing an instrument that has been rigorously validated through a modern measurement model, this study offers a standardized tool that can be used by educators to identify specific areas where students' logical-mathematical reasoning may be lacking.

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v5i4.2596 Volume 5, No 4, October - December 2025, pp. 1720 – 1730

Conclusion

Overall, this study concludes that the adapted Logical–Mathematical Intelligence (LMI) questionnaire administered to 317 senior high school students is both valid and reliable based on Rasch Model analysis. The psychometric evaluation demonstrates strong instrument quality, as evidenced by the fulfillment of the unidimensionality criterion (33.3% raw variance explained) and excellent reliability levels (Cronbach's Alpha = 0.89; Item Reliability = 0.96). These findings indicate that the instrument consistently measures a single underlying construct, aligning with Gardner's theoretical framework, which positions LMI as a specific domain of intelligence centered on reasoning and problem-solving. The primary academic contribution of this study is the provision of a psychometrically standardized LMI questionnaire validated using the Rasch Model. This model enables both items and respondents to be mapped onto a linear interval scale, offering a more precise and accountable measurement tool for assessing scientific reasoning potential at the high school level—an essential need given that students' deductive reasoning abilities are often not yet optimal. However, this study has certain limitations, particularly the use of convenience sampling and the absence of initial content validity testing for the adapted instrument. Therefore, future research should incorporate expert validation and further exploration of Differential Item Functioning (DIF) to strengthen the generalizability and construct validity of the instrument.

Conflict of Interest

The researcher revealed that there was no conflict interest.

Authors' Contributions

L.H. conceptualized the research idea presented, designed the research instruments, and collected the data. The other two authors (W.R. and F.A.H.) actively contributed to the development of the theory, methodology, data organization and analysis, discussion of the results, and approval of the final version of the work. All authors confirm that they have read and approved the final version of this manuscript. The percentage contributions for the conceptualization, drafting, and revision of this paper are as follows: L.H.: 40%, W.R.: 30%, and F.A.H.: 30%.

Data Availability Statement

The authors state that the data supporting the findings of this study will be made available by the corresponding author, [L.H.], upon reasonable request.

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