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Measuring the character construct of pancasila student profiles in the independent learning curriculum in elementary schools: Confirmatory factor analysis

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Abstract Student character development through the Pancasila Student profile is a priority in the Indonesian education system, especially in Elementary Schools. However, understanding of the acceptance and application of the six main aspects of the Pancasila Student profile such as religiosity, global diversity, mutual cooperation, independence, critical thinking, and creativity is still limited. The Independent Learning Curriculum increasingly emphasizes the importance of strengthening this character in schools. This study was conducted to measure the character construct of the Pancasila Student profile by focusing on these six aspects. Through quantitative methods, data were collected from 120 students in four public elementary schools in Baubau City using a questionnaire, then analyzed using confirmatory factor analysis using SPSS to measure the character construct of the Pancasila student profile. The results of the study showed that of the six aspects of character construct, religious and independent characters had stronger acceptance among students. Religiosity describes students' spirituality and faith, while independence shows students' ability to think and act independently. Both develop in accordance with the expectations of the Independent Learning Curriculum . However, the aspect of mutual cooperation, which emphasizes the spirit of cooperation and social solidarity, requires improvement. These findings show how important it is revisiting the strategy of teaching mutual cooperation in schools, considering that mutual cooperation is an important pillar in Indonesian culture and the profile of Pancasila Students. This study can be a reference for educators in designing more effective strategies, and emphasizes the need for further development with a wider sample size and school context, to strengthen the validity of the findings and provide more comprehensive recommendations in developing the profile of Pancasila Students in Indonesia.

Keywords: character, curriculum, profile of pancasila students, education, validity & reliabilty, model fit

1. Introduction

As time progresses, national challenges and changes become more complex. People view education as the primary element that can guide societal transformation and enhance quality of life (Hamduuna et al., 2023). This is in accordance with the function of national education as regulated by Law No. 23 of 2003, Article 3 concerning the National Education System, which reads, "National education aims to develop the potential of students to become human beings who believe in and obey God Almighty, have noble character, are healthy, knowledgeable, capable, creative, independent, and become democratic and responsible citizens" (Hilmi & Summiyani, 2023). Therefore, education must develop not only knowledge but also better behavior and character (Ganda Putri, 2022). However, various challenges, including the curriculum development process, frequently impede the achievement of educational goals (Sari, 2022). The curriculum, which is considered the core of education, continues to change to adapt to social, cultural, political, economic, and science and technology dynamics (Soleman, 2020). We expect the curriculum to achieve educational success.

The absence of true education in Indonesia and the impact socioculture, systems, politics, economy, science, and technology necessitate curriculum modifications. In addition to a strong curriculum, successful education necessitates the interconnection of all educational components (Sulistyorini, 2018). Curriculum development that is relevant to local, national, and global conditions is important for educational success (Destriani, 2022). Although many government policies discuss the importance of character development in education,few studies have specifically explored how curriculum changes affect student character development at various levels of education.In an effort to strengthen character education, the government launched various initiatives, including the National Character Education Movement and the Character Education Strengthening Program (PPK) in 2016 (Krisnawati et al., 2024). The attitudes, values, and mindsets developed through social interaction influence character, transforming it into an individual identity (Yulianti & Sulistyowati, 2018). The Pancasila Student Profile then

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emerged as part of an effort to improve the quality of education that emphasizes character building. Although various initiatives such as the National Character Education Movement and the Character Education Strengthening Program,exist research evaluating the concrete impact of these initiatives on the development of student character at various levels of education is lacking.

All educational levels, from kindergarten to high school, apply the Pancasila Student Profile. Idrus et al. (2023) In 2022, the design of the new educational paradigm adheres to the principle of differentiated learning, taking into account the needs and stages of development. The government has recently developed independent learning curriculum (Vhalery et al., 2022). The independent curriculum focuses on developing student profiles to instill the soul and values found in the Pancasila principles in their lives (Symbolon, 2023). One of the schools that uses the independent learning curriculum in Baubau City is SD Negeri 2 Bataraguru. The Independent Learning Curriculum focuses on character formation through the Pancasila student profile (Irawati et al., 2022).

According to the principal, Mrs. Hamiyah, "This independent curriculum contains a term called EUOC (Operasional Curriculum of Education Units), which is the basis for learning in schools, which will later be described as CP (Learning Achievements), TP (Learning Objectives), and ATP (Learning Objective Flow)." Ministerial Decree 1177/M/2020 states that the purpose of the curriculum is to strengthen skills and personalities with the Profile of Pancasila students (Laghung, 2023) SD Negeri 2 Baadia implements two curricula for independent learning: the Independent Learning Curriculum in grades 1 and 4, and the K13 Curriculum in grades 2, 3, 4, and 6. The purpose of using the Independent Learning Curriculum at SD Negeri 2 Baadia is to strengthen the character of students (Yulia et al., 2023). Introduced in 2022, the Independent curicculum targets character strengthening through the six main dimensions of the Pancasila Student Profile: faith and devotion to God Almighty, global diversity, mutual cooperation, independence, critical thinking, and creativity (Rachmawati et al., 2022). Various schools, including SD Negeri 2 Bataraguru in Baubau City, implement the independent curriculum, using the EUOC (Education Unit Operational Curriculum) as the basis for learning (Irawati et al., 2022). This curriculum aims to strengthen the character of students in accordance with the principles of the Pancasila Student Profile, especially through the Pancasila Student Profile Strengthening Project (P5) program (Yulia et al., 2023).

The independent learning curriculum itself focuses on character education for students. Prior to implementing the independent learning curriculum, the school had already incorporated character education into its curriculum. For example, the school encourages students to maintain the school's cleanliness, refrain from causing harm to plants, and practice discipline in time. The Pancasila student profile is used. The novelty of this study lies in its focus on measuring the character of the Pancasila student profile at the elementary school level and examining the Pancasila student profile with a focus on educators. This study focuses on the analysis of students. Additionally, this study employs confirmation factor analysis as its methodological approach to measure the variables in the Pancasila Student Profile Strengthening Project (P5). The study by Yulia et al. (2023) different from others, discussing the supporting and inhibiting factors in the formation of student character profiles based on Pancasila. Pancasila students strive to align their understanding and character with the values of Pancasila, ensuring that Pancasila continues to serve as the foundation of their ideology (Ulandari & Rapita, 2023).

This study aims to check construction of the Pancasila Student Profile character integrated into the Independent Learning Curriculum in Elementary Schools. This approach is carried out to test the validity and reliability of the measurement instrument through Confirmatory Factor Analysis (CFA) and to provide practical guidance for strengthening the implementation of the curriculum in shaping student character according to Pancasila values. We expect this study to deepen our understanding of the implementation of Pancasila students' character at the elementary school level, particularly within the context of the independent learning curriculum, ensuring that Pancasila continues to serve as the foundation of education in Indonesia.

2. Method

This study uses a quantitative approach and employs confirmatory factor analysis to demonstrate the measurement model of Pancasila student character profiles in elementary schools. We proved and verified several factors underlying the research variables.

2.1. Samples and data collection

Four elementary schools in Baubau City and the data collection site provided sample for this study. The adequacy of the sample used influences the suitability of the model in factor analysis (Aulia et al., 2018). Therefore, the adequacy of the sample must be considered. To obtain reliable data for factor analysis (Dwitasari et al., 2020), it may involve participants numbering more than one hundred or five times the number of items analyzed. This perspective led to the selection of 120 participants as the sample size for this study. It is considered that the sample size is sufficient to obtain data with an accurate and valid model. The characteristics of the Pancasila Student Profile are the variables studied in this research. This study primarily observes elementary school students. This study uses six indicators and 49 items to measure the variables (Table 1). The six indicators are religious diversity, mutual cooperation, independent reasoning, critical thinking, and creativity; each indicator involves several items to be measured.

Table 1 Distribution of indicators and items.

Indicator	Measurement Items	Code
Religion	I am used to performing fardhu prayers	R1
	I like helping friends who are in trouble	R2
	I care about friends	R3
	I truly respect my parents at home	R4
	I respect the teachers at school	R5
	I respect my school friends	R6
	I value my friends' opinions in class discussions.	R7
	I respect the beliefs or religion of my friends at school	R8
	I like cleaning the school yard	R9
	I throw the trash in its place	R10
Global Diversity	I know the culture of the Buton people	KG1
	I appreciate the culture of the society where I live.	KG2
	I am nationalistic and maintain noble culture	KG3
	Love the original culture and traditions of Indonesia	KG4
	Respecting other nations' culture	KG5
	Love harmony and peace in society	KG6
	As a citizen, I love the state ideology (Pancasila)	KG7
Mutual cooperation	I am used to working together with the theme in cleaning the school environment	BR1
	Donate to help friends in need	BR2
	Mutual cooperation in decorating the classroom	BR3
	Participating in tree planting activities together in the school environment	BR4
	Work together to maintain the good name of the school	BR5
	Working together to clean the toilets at school	BR6
	Working together to clean the gutters at school	BR7
	Working together to clean the library space	BR8
	Work together to maintain the cleanliness of the school garden	BR9
	I cleaned the prayer room at school with my friends.	BR10
Independent	I study by myself at home	MD1
	I dare to speak in front of the class	MD2
	If there is homework at school, I do it myself at home	MD3
	I return the learning tools in the classroom to their place.	MD4
	I arrived at school on time before the lesson started.	MD5
Critical thinking	If I do not understand what the teacher explains in class, I always ask.	BK1
	I am active in learning discussions in class	BK2
	Understand the learning explained by the teacher	BK3
	I like reading books	BK4
	Able to express opinions in front of the class	BK5
	Listening and respecting other people's opinions	BK6
	Have a high sense of curiosity	BK7
	Not afraid to be wrong	BK8
	Do not rush to conclusions	BK9
Creative	I love challenges and new things	K1
	I like turning trash into handicrafts	K2
	I like dancing	K3
	I love to imagine	K4
	Creating an art project	K5
	I participated in a short story writing competition	K6
	I am adaptable	K7

This study involved 120 respondents from 4 schools and aimed to evaluate the characteristics of students on the basis of six predetermined indicators. Among the total respondents, the proportion of males was 39.17%, while the proportion of females reached 60.83%. These data indicate gender inequality in the composition of respondents, with more females than males. Through an analysis of these indicators, this study aims to provide deeper insight into the expected character values in the context of education in these schools. The following is the distribution of research samples (Table 2).

Table 2 Respondent caracteristic.

Elementary school	N	Man	%	Woman	%
SDN 2 Baadia	30	11	37	19	63
SDN 1 Wajo	30	14	47	16	53
SDN 2 Bataraguru	30	13	44	17	56
SDN 4 Katobengke	30	9	30	21	70
Total	120	47	39.17	73	60.83

This study icluded 120 respondents who completed the questionnaire. The questionnaire consisted of 49 items designed to measure six indicators of the Pancasila Student Profile. Each indicator reflects the character values expected in the formation of a student character. Data collection was conducted through a face to face survey, allowing direct interaction to ensure that the questionnaire was filled out accurately and achieved a high response rate. The measurement scale is used to classify the level of response. This questionnaire uses a scale of always, often, sometimes, and never. This approach also helps minimize the potential for measurement errors. The questionnaire instrument has been validated by experts in the field of education and shows good reliability. By involving teachers in the competion process, this study aims to provide an objective assessment of each respondent so that the results obtained reflect the expected characteristics of the Pancasila Student Profile. After the questionnaire was completed, the results were collected and analyzed by researchers to gain deeper insight into character values among students.

2.2. Data analysis

We used confirmatory factor analysis as the data analysis technique. For data analysis, SPSS and JASP software were used. Latent variables and indicator variables are part of confirmatory factor analysis. While we cannot directly form and construct latent variables, we can clearly observe and measure indicator variables.

3. Results and Discussion

The research results are based on the previously constructed variables, which include six aspects and 49 items.

3.1. Religion

The first indicator of religious character consists of 10 items. The results of the confirmatory analysis are presented in the model plot as follows (Figure 1).

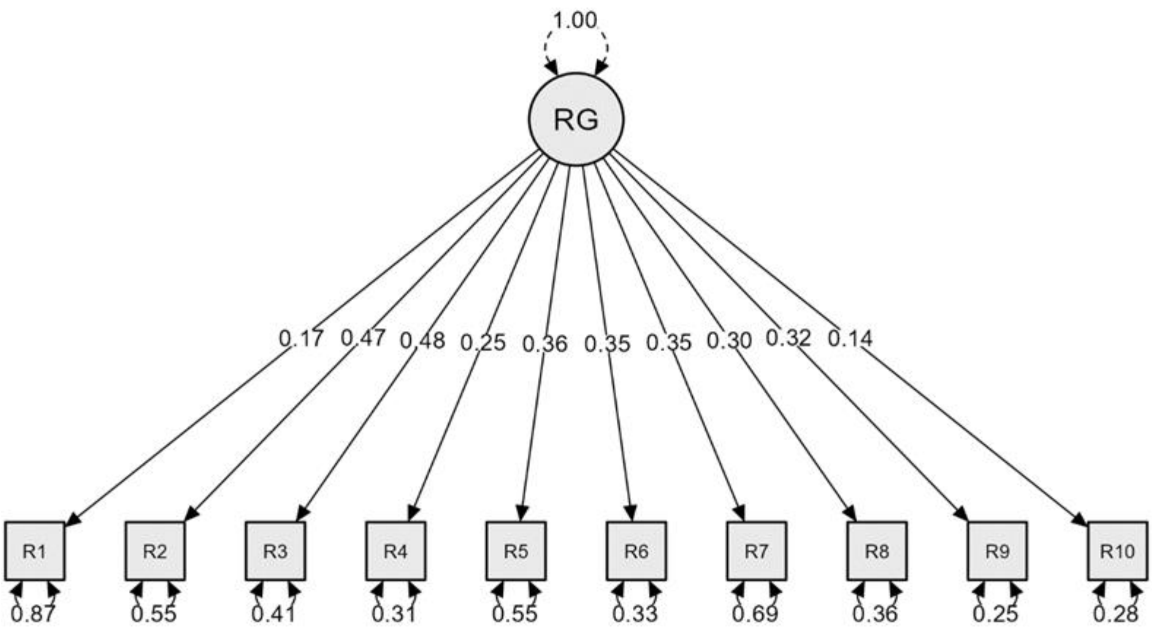

Figure 1 Religious variable construct.

According to the confirmatory factor analysis results, the measurement item (R3) "I care about my friends" "provides the greatest contribution to the religious character variables of students in elementary schools," as indicated by the factor loading coefficient. The measurement item (R3) "I care about my friends" has the highest factor loading. The statement "I care about friends" describes the presence of positive interpersonal relationships, where someone shows concern for the welfare of others. This concern is part of prosocial behavior, which plays an important role in strengthening social bonds and supporting emotional well-being. In Scopus-indexed research journals, this topic is often associated with the concepts of social support and empathy, both of which play key roles in an individual's mental well-being. For example in research on social support and well being studies published in Scopus journals have shown that social support from friends is significantly associated with improved mental health and emotional resilience. Empathy and Interpersonal Relationships: Other studies have shown that the ability to show concern or empathy for friends is associated with more satisfying and high-quality relationships. Empathy strengthens emotional bonds and helps create deeper and more meaningful relationships (Weiser et al., 2023).

Acording to a study in Scopus, prosocial behavior, such as caring for friends, is associated with increased life satisfaction and emotional well being. This behavior increases self-esteem and provides a sense of meaning in life because of its contribution to the well being of others (Panter-Brick & Eggerman, 2018). Thus, caring for friends not only strengthens interpersonal relationships but also has a positive effect on mental and emotional well-being, according to many studies indexed in Scopus. On the basis of the coefficient ω (Omega) = 0.684 and the coefficient α (Alpha) = 0.686, the reliability of the instrument is considered to be within the acceptable range. Although the alpha (α) value is generally considered satisfactory if it is above 0.70, an α value approaching the threshold (such as 0.686) is still acceptable and indicates fairly satisfactory internal consistency. Likewise, an omega (ω) value approaching 0.70 indicates that the instrument has sufficient reliability, although it isnot ideal. Overall, these two coefficients suggest that the instrument is quite reliable, but achieving higher standards may require a slight increase in reliability.

For example, a previous study by Howard et al. (1979) reported similar reliability for an instrument measuring critical thinking skills in elementary schools. Researchers often recommend minor item revisions or further development of the instrument to improve reliability in the future. The Scandinavian Journal of Educational Research published a study on the development of a student character instrument, which revealed similar findings, with omega and alpha values slightly below 0.70, yet deemed reliable enough for further analysis. Thus, the results of this study are consistent with those of published studies and provide evidence that the instrument can be further refined to achieve greater reliability. Two models are tested on the basis of the results of the Chi-Square Test: the baseline model and the factor model. The baseline model has a Chi-Square (X^2) value of 169.111 with 45 degrees of freedom (df). The factor model has a Chi-square (X^2) value of 45.686 with 35 degrees of freedom (df) and a p_value of 0.107. The p_value = 0.107 indicates that the factor model is not significantly different from the baseline model. Since the p_value is greater than 0.05, the factor model fits the data and there is no significant difference, indicating a major error in the model fit. Thus, the factor model can be accepted as appropriate for the data being tested

In similar studies, insignificant Chi-square and p_value values are often used as indicators that the factor model or structural model fits the existing data. One study by Bumpus et al. (2010) reported that a model fits well when the Chi-square value is low and the p_value is greater than 0.05. This is especially true when other fit measures such as the Compartive Fit Index (CFI) orRoor Mean Square of Approximation (RMSEA) are added. In addition Ramasubramanian (2011) asserted that insignificant p_values support that the model does not deviate substantially from the observed data, which is consistent with this finding. The analysis results show that the comparative fit index (CFI) and the incremental fit index (IFI) values above 0.90 indicate that the model has a satisfactory fit with the data. Generally, we use these two indices to evaluate a model's fit against the baseline model, with values exceeding 0.90 signifying a highly satisfactory fit. Tucker Lewis Index(TLI) and Non Normed Fit Index (NNFI)) values above 0.80 also support that the model has a satisfactory fit, although there is still room for improvement. Ideally, TLI and NNFI values above 0.90 would indicate a better fit, but values above 0.80 already indicate a fairly satisfactory fit. However, the Normed Fit Index (NFI)) value = 0.730 is slightly lower than the ideal value (0.90), which indicates that the model may not fit the data completely. In addition, lower values of Parsimony Normed Fit Index (PNFI)and Reltive Fit Index (RFI) indicate that although the model is generally a satisfactory fit, there are indications that the model may be too complex or have some fit issues. Overall, although some indices support a satisfactory fit, lower values of NFI, PNFI, and RFI indicate some complexity or imperfections in the model fit.

The findings of the analisys of index value for model fit such as CFI, IFI, TLI, and NFI, which are used to evaluate model fit, align with various studies in the scientific literature that also use these indices to measure model fit. Mustafa et al. (2020) proposed CFI and IFI values above 0.90 as indicators of excellent fit, a finding that aligns with yours. These indices have become the standard for measuring model fit, especially in structural models. Morever, TLI and NNFI values above 0.80, although not yet reaching the ideal threshold (above 0.90), are also considered acceptable according to other studies, as expressed by Byrne (2016). In this context, they argue that although values above 0.90 are better, values above 0.80 are still acceptable, especially in more complex models or with smaller sample sizes. NFI values below 0.90, as you found (0.730), reflect findings from a study by Nam et al. (2018), where lower NFI values may indicate that the model does not fully fit the data. However, the NFI is also known to be sensitive to sample size, so in small samples, this index may not reach its ideal value. The study shows that the

Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the sample-size adjusted BIC (SSABIC) are information criteria that are used to judge models on the basis of how well they fit and how complicated they are.

Lower values of these three criteria indicate a better model and a better fit with the data. AIC is used to compare multiple models, with the model with the lowest AIC value considered better in terms of the balance between fit and complexity. BIC: This method is similiar to AIC but imposes a greater penalty for model complexity. Lower BIC values indicate a simpler model and a better fit to the data. SSABIC: This is a version of the BIC adjusted for sample size. It provides additional information about how the model performs at larger or smaller sample sizes, with lower values also indicating a better model. Overall, lower values for AIC, BIC, and SSABIC indicate that the model fits the data better and is less complex, making it more efficient and appropriate for prediction or generalization.

The literature frequently uses the AIC (Akaike Information Criterion) to compare several models with varying complexities. Harlyan et al. (2021) demostrated the usefulness of the AIC in balancing model fit to data and model complexity. They emphasize the importance of choosing the model with the lowest AIC because it shows that the model is able to explain the data without adding unnecessary parameters. The Bayesian Information Criterion (BIC) imposes a greater penalty on model complexity than AIC. Studies that consider large sample sizes often employ BIC (Burnham & Anderson, 2004). Research reveals that BIC tends to select simpler models, particularly when the sample size is large. In your study, a lower BIC value signifies that the tested model not only fits the data but also has an efficient number of parameters.The Sample Size Adjusted Bic (SSABIC) adjusts the BIC value, taking into account the sample size. In this context, research by Knowles et al. (2023) empasized that SSABIC provides a more accurate fit for models tested on various sample sizes. A lower SSABIC value indicates that a model not only fits the data but is at olso efficient for samples of various sizes, both large and small.

An RMSEA less than 0.06 indicates a decent model fit, with a p_value supporting an excellent fit to the data. An SRMR below 0.08 also indicates a satisfactory fit. A higt GFI and MFI indicate a satisfactory fit with the data. A low ECVI indicates a favorable model in terms of cross-validation. Overall, the results of the analysis indicate that the tested model has a satisfactory fit with the data. Fit index values such as CFI, TLI, IFI, and RMSEA support the model's suitability. Fit indicator values such us NFI and PNFI suggest potential areas for model improvement or simplification. The reliability of the instrument is also within the acceptable range, indicating that the data collected are consistent and reliable. The results of the analysis above are in line with the findings of research conducted by Xia & Yang (2019) which suggestes that an RMSEA value below 0.06 indicates a model with a good fit to the data. RMSEA is considered one of the most important indicators because it takes into account model errors and corrects for large sample sizes. Sitanggang et al. (2022) suggested that complex models can lead to decreased NFI and PNFI, emphasizing the need for model simplification or modification to improve fit.

3.2. Global diversity

The second indicator, which measures the character of mutual cooperation, comprises seven items. The results of the confirmatory analysis are presented in the model plot as follows (Figure 2).

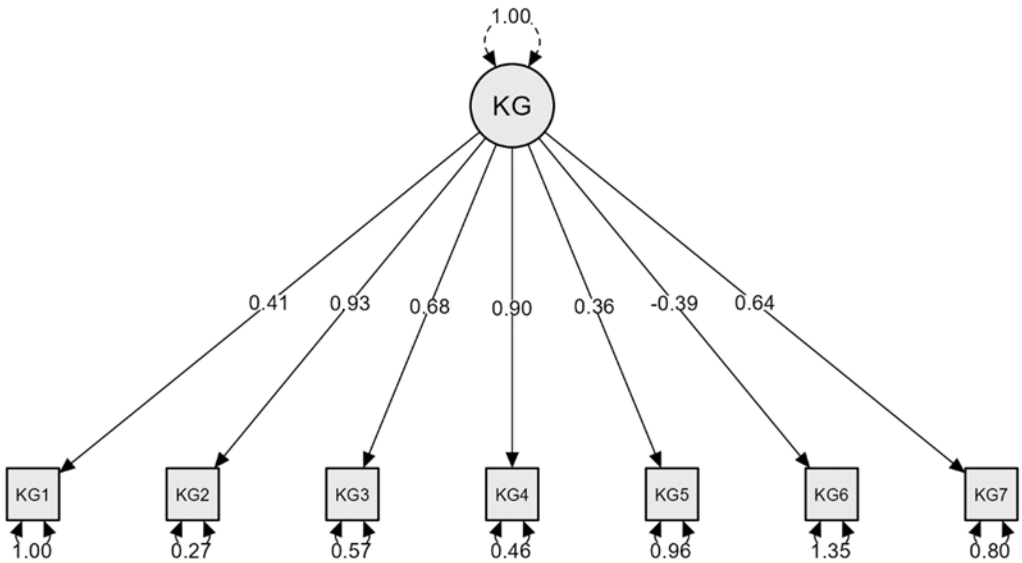

Figure 2 Global diversity variable construct.

The confirmatory factor analysis reveals, using the load factor coefficient, that the measurement item (KG2) is "I appreciate the culture of the community where I live." The findings of the study above indicate that a confirmatory factor analysis is used to ensure that the items used in the instrument actually measure the construct. The largest contribution of item KG2 to the variable of students' global diversity character indicates that this item is more representative than other items in explaining cultural diversity in students. On the basis of the coefficients ω (Omega) = 0.633 and α (Alpha) = 0.669 for the KG instrument, its reliability is classified as slightly low but still within acceptable limits. The alpha (α), which is below the ideal threshold of 0.70, indicates that the instrument may have less than optimal internal consistency. In other words, the variability between items in the instrument may still be quite high, and improvements in some items or aspects of measurement can improve overall consistency. The omega (ω) value, which is 0.633, also indicates that although the reliability of the instrument is not bad, there is room for improvement. Overall, this instrument requires review and possible modification to achieve higher reliability and ensure that the measurement is more consistent and accurate. Many studies have established an α value above 0.70 as the minimum standard for adequate internal consistency (Smith et al., 2000). A value below this threshold signifies variability among the measurement items, indicating the need for modifications to enhance the instrument's performance. (Bailey & Johnston, 1983) suggested that omega provides a more comprehensive picture than alpha does because it takes into account the factor structure of the measurement items. However, an ω value below 0.70 also indicates that there is room for improvement in the instrument, either in terms of refining the items or rephrasing the measurement aspects.

The results of the Chi-square Test indicate the testing of two models: the baseline model and the factor model. The baseline model has a Chi-square (X^2) value of 269,500 with 21 degrees of freedom (df). The factor model has a Chi-square (X^2) value of 49,120 with 14 degrees of freedom (df) and a p_value <0.001. A p_value <0.001 indicates that there is a significant difference between the factor model and the baseline model. In other words, the factor model significantly outperforms the baseline model, and the significant difference suggests that the factor model accurately represents the data. However, the significance of this difference also highlights the possibility that the factor model is too complex or needs further adjustment. Overall, these results show that the factor model outperforms the baseline model, but the significant difference suggests that the model may require further evaluation to achieve optimal fit. The above analysis also discusses the relationship between the Chi-square test and additional fit measures in evaluating structural models. Research by Bentler (1990) shows that model assessment cannot rely solely on the Chi-square value but must consider a broader range of fit indices to obtain a more comprehensive picture of model fit.

As indicated by the fit indices and Comparative Fit Index (CFI), as well as the Incremental Fit Index (IFI) values less than 0.90, the model fit is less than optimal. Values below this threshold suggest that the model might not fully fit the data and that adjustments might be needed to enhance the fit. Tucker Lewis Index (TLI) and Non Normed Fit Index (NNFI) below 0.80 indicate that the model fit is also relative poor. Both TLI and NNFI are generally considered ideal if they are above 0.90, and values below 0.80 suggestes that the model may not accurately reflect the actual data structure. The Normalized Fit Index (NFI), which is better than TLI and NNFI but still below the ideal threshold of 0.90, indicates that the model has a sufficient fit but still needs improvement to achieve optimal fit. Parsimony Normede Fit Index (PNFI) and Relative Fit Index (RFI), which also have low values, indicate that the model may still be too complex or have some fit issues. This means that there is potential to improve the model to better fit the data, perhaps by simplifying the model structure or correcting the model specification. Overall, the fit index values indicate that the current model does not fully fit the data and needs improvement. The model may need adjustments to improve the fit and achieve a better level of fit. These findings sugest implementing steps in the development of structural models. For example, Echtenkamp & O'Hanlon Curry (2015) suggest that model revision is often necessary when the fit index is below an acceptable threshold, especially to improve the overall fit of the model.

The study shows that the Akaike Information Criterian (AIC), the Bayesian Information Criterian (BIC), and the Sample-Size Adjusted BIC (SSABIC) are information criteria that are used to judge the quality of a model by examining how well it fits the data and how complicated it is. AIC and BIC penalize the number of parameters in the model, so models with lower values are considered better because they indicate a satisfactory fit to the data while maintaining lower complexity. Sample-Size Adjusted BIC (SSABIC) is a version of the BIC adjusted for sample size, giving additional consideration to sample size in model evaluation. Lower values indicate a better model considering different sample sizes. In general, lower AIC, BIC, and SSABIC values indicate that the model is better because it provides a better balance between fit and complexity, as well as predictive ability. However, it is important to consider these values together with other fit indicators such as CFI, TLI, RMSEA, and SRMR to obtain a more comprehensive model evaluation. Combining information criteria with fit indicators helps ensure that the selected model not only fits the data but is also not too complex and has good generazability.

In general, a combination of lower values for AIC, BIC, and SSABIC indicates that the model has a good fit to the data while maintaining lower complexity. Overly complex models can lose generalizability, the ability to apply to new data or data outside the tested sample. However, to obtain a more comprehensive model evaluation, it is important to consider these values in conjunction with other fit indicators such as the CFI, TLI, RMSEA, and SRMR. These fit indicators provide additional information about how well the overall model fits the data (Xia & Yang, 2019). For example, high CFI and TLI values indicate that the model has a very good fit to the data, where low RMSEA and SRMR values indicate small averaging errors. By combining information criteria and fit indicators, researchers can ensure that the selected model not only fits the data but also has excellent predictive ability and is not too complex. This will increase the validity and reliability of the research findings.

A high RMSEA (0.144) indicates that the model may not fit well. The very small RMSEA p_value indicates a poor fit between the model and the data. SRMR below 0.08 indicates a satisfactory model fit. A high GFI indicates that the model fits the data, but high MFI indicates a poor fit. The low ECVI indicates that the model may have excellent cross-validation ability.

The analysis results show that the tested model has issues with data fit. The values of fit indices such as the model may not fit, according to CFI, TLI, and RMSEA. The reliability of the instrument is also slightly low, indicating the need for improvements to increase internal consistency. We may need to make model adjustments or revisions to enhance the model fit and increase the instrument's reliability. Many studies in the literature discus the importance of model adjustment in structural analysis. For example, research by Echtenkamp & Curry (2015) shows that model revisions based on fit analysis results are an important step to ensure the model's validity in explaining the relationships between variables.

3.3. Working together

The third indicator, which represents the character of mutual cooperation, comprises 10 items. The results of the confirmatory analysis can be presented in the following plot model (Figure 3).

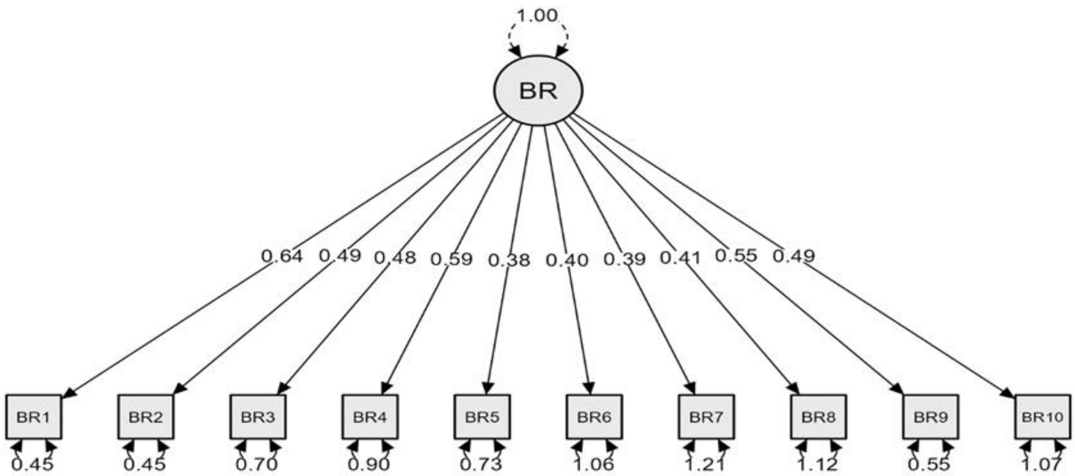

Figure 3 Mutual cooperation variable construct.

The results of the confirmatory factor analysis, indicate that the factor loading coefficient shows that the measurement item (BR1) "I am used to working together with the theme in cleaning the school environment" makes the greates difference how cooperative elementary school students are with each other. Several studies have shown that involvement in joint activities, such as tree planting, contributes positively to the development of students' character. For example, research by Lickona (2013) in the journal "Journal of Character Education" explains how collaborative activities in the school environment help build social values and character in children. conducted research in "The Journal of Educational Research" which emphasized the positive impact of community-based project-based learning, Such us tree planting activities, student cooperation, engagement, and positive character development (Rodríguez-Zurita et al., 2025). In the journal "Environmental Education Research" that revealed that environmental activities with active student participation can enhance social responsibility and mutual cooperation, which aligns with the finding that item BR4 significantly contributes to the measured construct.

The values of the Coevicient ω (Omega) = 0.719 and Coevicient α (Alpha) = 0.747 indicate that the instrument used has good internal consistency. A Coevicient ω (Omega) of 0.719 indicates that the instrument has good reliability, with a value approaching the ideal threshold of 0.70 indicating that the instrument is quite consistent in measuring the intended construct. The instrument's Coevicient_(alpha) of 0.747 demonstrates strong internal consistency, surpassing the commonly used minimum threshold of 0.70 to evaluate its quality. This value indicates that the items in the instrument tend to correlate well with each other and provide stable measurements. Overall, these values demonstrate the measuring instrument's adequate reliability and its consistent ability to measure the targeted variables. This tool can be considered reliable for research purposes or specific applications. Research conducted by Tavakol et al. (2011) in the "International Journal of Medical Education," an alpha value above 0.70 generally indicates that an instrument has good reliability. They also emphasize the importance of considering Alpha and Omega together to provide a more complete picture of the reliability of the instrument. Research by (Bernstein & Nunnally, 1994) in the book "Psychometric Theory" empashizedhat good internal consistency is an important indicator in psychological measurement. They show that higher reliability leads to more stable measurements, which supports the use of instruments in academic and practical research. An article by Cortina (1993) in the "Journal of Applied Psychology" developed the concept of reliability and decribed various methods, including the use of alpha and omega, to assess the quality of a measuring instrument. Cortina emphasized that instruments with high omega and alpha values indicate that the items in them are well correlated, which means stable and consistent measurements.

The Chi-square Test results show the evaluation of two models: baseline model and the factor model. Chi-square is used in the basic model. (χ^2) value of 297.964 with 45 degrees of freedom (df). The factor model has a chi-square ($\chi 2$) value of 128.657 with 35 degrees of freedom (df) and a p_value <0.001. A p_value <0.001 indicates that there is a significant difference between the factor model and the data, In short although the factor model may show improvements over the baseline model, a very small p_value indicates that the model does not fully fit the data. A small p-value indicates that the factor model still does not fit the data well, although this significant difference shows that the factor model is very different from the baseline model. This finding indicates that the model may need further adjustment or refinement to better reflect the actual structure of the data. Research by Hooper et al. (2008) states that a significant Chi-square value often indicates that the model does not fully fit the data. To get a better picture of the model fit, they suggest using additional fit indices such as CFI, TLI, and RMSEA. Factor Model vs. Baseline: A study by Kline, (2018) in " Principles of Structural Equation Modeling and Its Techniques " emphasized that the comparison between the factor model and the baseline model is an important step in model evaluation. Kline explained that a significant difference may indicate that the factor model is better; it is important to remember that the model may require further adjustment to achieve optimal fit. Model Fit in Research: In the context of education and psychology. Saeedy et al. (2019) in "Research in Social and Administrative Pharmacy" emphasizing the importance of conducting a thorough examination of the model, especially when factor analysis is used. They remind researchers not only to rely solely on the Chi-square value but also to consider other measures of model fit to ensure the validity of the results.

The results of the model evaluation based on the fit index indicate that the model does not meet the standards of excellent fit. The Comparative Fit Index (CFI) of 0.630 and the Tucker-Lewis Index (TLI) or Non-Normed Fit Index (NNFI) of 0.524 indicate that the tested model exhibits a low level of fit. The CFI value, which falls far below the recommended threshold (≥ 0.90), suggests that the model does not adequately represent the empirical data, while the very low TLI value reinforces that the model's performance in explaining the data is not substantially better than that of a random or baseline model. The Normed Fit Index (NFI) of 0.568 indicates that the model does not adequately fit the data and performs even worse than a random model. The Relative Fit Index (RFI) of 0.445 also reflects a very low level of fit, further emphasizing the model's weakness in representing the empirical data. The Incremental Fit Index (IFI) of 0.644, although slightly higher than the other indices, remains below the recommended standard, thereby suggesting a poor level of model fit. Similarly, the Relative Noncentrality Index (RNI) of 0.630, which is consistent with the Comparative Fit Index (CFI), demonstrates that the model fails to achieve an acceptable fit to the data. Overall, these values indicate that the model does not fit the data used and needs improvement to improve its fit. On the basis of the results of the model evaluation, it is necessary to conduct a suitability index evaluation as stated by Gerbing & Anderson (1992). A low CFI can be detrimental to data interpretation, requiring researchers to make adjustments to the model to better reflect the data. According to. (Kline, 2014) it is necessary to revise the model to improve fit, which may result in the exclusion of some important factors or relationships. Research by (Hooper et al., 2008) confirmed that models with NFI Values less than 0.90 require significant adjustment. A low RFI also indicates unnecessary complexity in the model. Incremental Fit Index (IFI) = 0.644 and Relative Noncentrality Index (RNI) = 0.630: Although slightly higher, these values still indicate that the model requires further improvement, in accordance with Schreiber (2010) opinion about the importance of better IFI values to ensure model fit.

We evaluate and compare models via the Akaike Informatio Criterion (AIC)), Bayesian Information criterian (BIC), and Sample-Size Adjusted BIC (SSABIC) values,with a focus on the balance between model fit and complexity. High AIC, BIC, and SSABIC values indicate that the model may be too complex or not a satisfactory fit. These high values may indicate that the model contains too many parameters compared with the improvement in model fit or that the model does not perform well enough to accurately reflect the data. Lower AIC, BIC, and SSABIC values indicate a better model because of a better balance between fit and complexity. Lower values indicate that the model is able to achieve a better fit to the data while maintaining a more efficient number of parameters. Overall, while the AIC, BIC, and SSABIC are useful for comparing models, lower values of these criteria indicate that the selected model is more efficient and has a better balance between fit and complexity. High values of these criteria indicate a need to reevaluate the model or seek simpler or more appropriate alternatives. Overall, the AIC, BIC, and SSABIC values serve as important indicators in evaluating and comparing models. Although they provide useful information, it is important to consider these results in conjunction with other fit indices (such as CFI, RMSEA, etc.) to obtain a more comprehensive picture of the model's performance. If the values of these criteria are high, the researcher needs to reevaluate the existing model or find a simpler and more appropriate alternative for the data used. The use of these criteria is also comparable to before research, as stated by Zink et al. (2005), who emphasized the importance of choosing a model that balances complexity and fit to obtain valid and reliable results.

We can conclude from the evaluation results, which use various model fit indices, that the model does not adequately fit the data. The Root Mean Square Error of Approximation (RMSEA) of 0.149 is far above the recommended threshold (≤ 0.06), indicating that the model does not adequately fit the data. A higher RMSEA value reflects a poorer model fit. The 90% confidence interval (CI), with a lower bound of 0.122 and an upper bound of 0.177, further confirms that the RMSEA consistently falls within a range that signifies poor model fit. The very small p-value of 1.612×10^{-8} provides additional evidence that the model does not adequately represent the data. The Standardized Root Mean Square Residual (SRMR) of 0.114, which exceeds the acceptable cutoff of 0.08, indicates substantial discrepancies between the predicted and observed values, thus reflecting poor fit. The Goodness of Fit Index (GFI) of 0.963 suggests a relatively good fit; however, its interpretation in isolation is insufficient, particularly given that most of the other indices strongly indicate poor model fit. Similarly, the McDonald Fit Index (MFI) of 0.679 demonstrates that, overall, the model cannot be considered an adequate representation of the data. The

Expected Cross Validation Index (ECVI) value of 1.559 indicates the model's ability to predict new data. A lower ECVI value reflects a better model in representing the population and suggests a higher potential for generalizability.

Lower values typically indicate a better model at predicting new data, and in this case, the ECVI value indicates that the model may not be ideal for prediction. Overall, while one index (GFI) indicates a fairly satisfactory fit, most of the other indices, especially RMSEA and SRMR, indicate that the model does not fit the data well. We need to improve or modity the model to enhance the fit. Overall, the results of the analysis show that although the GFI shows a fairly good fit (Zheng et al., 2020). Most other indices, especially RMSEA and SRMR, showing the model's inconsistency with the data. This confirms that the current model has several problems in terms of fit. Therefore, we need recommendations to enhance the model. We may need to make adjustments to the model structure, such us adding potentially missed variables or deleting insignificant parameters, to enhance the model fit. We advise researchers to utilize additional fit indices such us CFI, TLI, and NFI to gain a comprehensive understanding of the model's performance. If the model does not fit after adjustment, the study's theory or framework may need to be rethought.

3.4. Independent

The fourth indicator for the idependent character consists of five items. The results of the confirmatory analysis are presented in the model plot as follows (Figure 4).

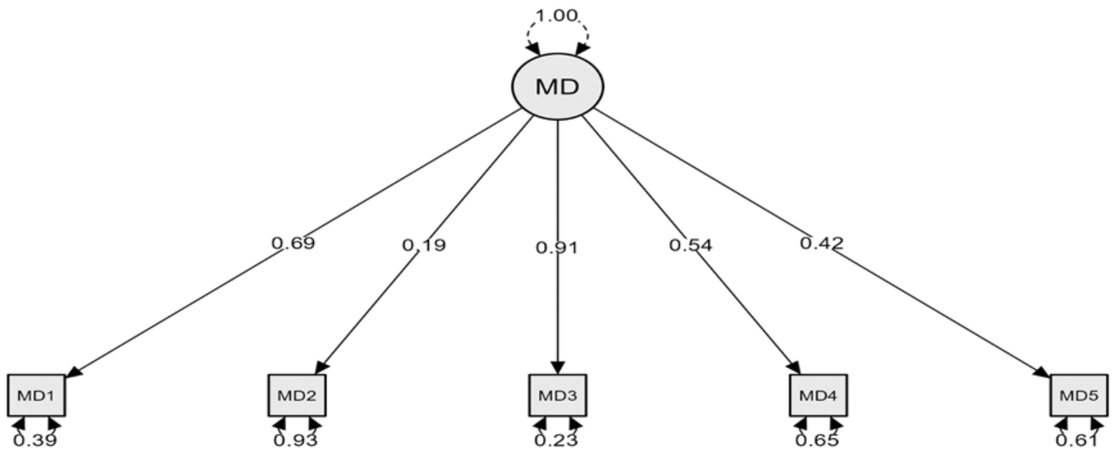

Figure 4 Independent variable construct.

According to the confirmatory factor analysis results, the measurement item (MD3) "If there is homework at school, I do it myself at home" contributes the most to the independent caracteristic variable of elementary school students, as indicated by the factor loading coefficient. According to the results of this study, the measurement item (MD3), "If there is homework at school, I do it myself at home," has a significant loading coefficient, indicating that this behavior is an important indicator of students' independent character in elementary school. This is in line with research by Topping & Trickey (2007). Who reported that student involvement in managing their learning environment, including tidying up and returning learning tools, contributes to the development of independent character. In addition, the research conducted by (McClelland et al., 2021) shows that responsible behavior in the educational context supports the development of student independence, strengthening the importance of this measurement item in reflecting characteristic independent. This study also supports the findings of (Blagoveshchenskaya et al., 2017). Who highlited that properly returning learning tools demonstrates not only independence but also respect for the learning environment and teaching materials, thereby enhancing students' discipline and responsibility. Therefore, it is important to emphasize this behavior in the elementary education curriculum to strengthen students' independent character.

The value of the Coeficient ω (Omega) = 0.718 and Coeficient α (Alpha) = 0.706 indicate that the measurement instrument has excellent internal consistency. A Coeficient ω (Omega) of 0.718 indicates that the instrument has excellent reliability, approaching or slightly exceeding the threshold of 0.70. This finding indicates that the items in the instrument are well correlated and consistent in measuring the intended construct. A Coeficient α (Alpha) of 0.706 also indicates solid internal consistency, although it is slightly below the ideal threshold of 0.70. This value indicates that the instrument is quite stable in term of measurement and reliable. Overall, these values demonstrate the Reliability of the Measurement Instrument. This instrument has adequate internal consistency and can be considered effective in measuring the targeted variables. Ortega (2010) research aligns with this finding, emphasizing the crucial role of the measurement instrument's reliability in ensuring the validity of the obtained results. The Coeficient α (Alpha), which is slightly below the ideal threshold, can indicate that although the instrument has good internal consistency, there is still room for improvement. Research by Tavakol et al. (2011) al Sempasized the importance of the omega value in assessing reliabilityThey argue that the level omega value indicates that the tool is reliable for measuring the targeted construct. This is in line with the omega (ω) coefficient obtained in this study, which is 0.718, indicating that the instrument possesses an adequate level of internal consistency.

The Chi-squre results compare the baseline model and the factor model. The baseline model has a Chi-square (χ^2) value of 154.972 with 10 degrees of freedom (df). The factor model has a Chi-square (χ^2) value of 20.141 with 5 degrees of freedom (df) and a p_value of 0.001. The p_value = 0.001 indicates that there is a significant difference between the factor model and the data. This means that although the factor model may show improvement over the baseline model, a small p_value indicates that the factor model does not fully fit the data. With a small p_value, the difference between the data and the proposed model is statistically significant. This indicates that the factor model may not fully represent the current data structure. Overall, these results indicate that although the factor model may be better than the baseline model, it still falls short in terms of data fit. This indicates the need for further adjustments to improve the model's relevance with current data. Additional fit measures. Overall, although the factor model shows improvements Over the baseline model, the analysis results show that the model still has gaps in matching the data. We expect to improve model compatibility with the existing data by considering recommendations from relevant literature and making adjustments to the model. Making this adjustment it is important to know that the model accurately reflects the actual data structure, thereby improving the credibility and consistency of research results (Schreiber et al., 2006).

On the Basis of the evaluation results using various fit indices, this model shows a fairly satisfactory fit but still needs some improvements. The Comparative Fit Index (CFI) of 0.896 is close to the recommended threshold (≥ 0.90), indicating that the model demonstrates a reasonably good fit to the data, although it does not reach the ideal level. The Tucker-Lewis Index (TLI) or Non-Normed Fit Index (NNFI) of 0.791 falls below the expected standard, suggesting that the model does not fit optimally and requires improvement to enhance its adequacy. The Normed Fit Index (NFI) of 0.870 also reflects a moderately good fit but remains below the ideal cutoff, leaving room for further refinement. In contrast, the Relative Fit Index (RFI) of 0.740 indicates a poor level of fit, underscoring the need for substantial modifications to achieve a more acceptable model. The Incremental Fit Index (IFI) of 0.899 is close to the anticipated threshold, suggesting a reasonably good fit, though still slightly below the ideal criterion. Similarly, the Relative Noncentrality Index (RNI) of 0.896 demonstrates that the model achieves an overall reasonably good fit, although further improvements remain possible.In general, although several indices, including CFI, IFI, and RNI, are close to the expected values, other indices, such as TLI and RFI, indicate that the model has not achieved optimal fit. This model can be considered quite good but still needs improvement to achieve an ideal fit. Overall, although some indices indicate that the model has a fairly satisfactory fit, lower values of certain indices indicate room for improvement. We can improve model fit by making appropriate adjustments on the baisi ofthese findings and guidance from the relevant literature, which will enable the model to more accurately reflect the actual data structure. Referring to the guidance from Edsall (2023) adjustments to the model structure by adding relevant variables or removing insignificant parameters can help improve model fit.

The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC)), and Sampe-Size Adjusted BIC (SSABIC) values are information criteria that provide a measure of the penalty for model complexity. These criteria help in evaluating and comparing models in the following ways: The AIC, BIC, and SSABIC measure the balance between model complexity and fit. Lower values indicate that the model is better in terms of this balance; that is, Good data compatibility is provided by this model. while maintaining low complexity. Lower values of AIC, BIC, and SSABIC indicate that the model is better because it is more efficient in terms of the number of parameters available used to achieve a satisfactory according to the data. Models with these values tend to be simpler and easier to interpret. Higher values indicate that the model may be somewhat complex, contain more parameters, or not fit as well as more efficient ones.

However, these values still indicate that the model may be better than a poorer model compared with highly complex or inadequate alternatives. Overall, while higher AIC, BIC, and SSABIC values may indicate a somewhat complex model, these values still provide insight into the effectiveness of the model in achieving a balance between fit and complexity. A more comprehensive model evaluation requires consideration along with other criteria to determine the optimal model. Overall, the research findings on The values of SSABIC, AIC, and BIC emphasize the importance of balancing the fit and complexity of the model in research. Lower values indicate that the model is more efficient and easier to interpretin accordance with the relevant literature guidelines. This suggests that the use of criteria information similar to AIC, BIC, and SSABIC is a significant step in model evaluation process to ensure that the resulting model is not only appropriate but also simple and informative. Muthén & Asparouhov (2002) recommend that researchers consider these information criteria when comparing different models and the values of AIC, BIC, and SSABIC can offer valuable insights in choosing the most suitable model for a specific dataset.

On the basis of the evaluation results with various model fit measurements, a general description is as follows: Root Mean Square Error of Aproximation (RMSEA) =0.158. This value indicates poor model fit because it is far above the ideal threshold of 0.06. The 90% confidence interval range (0.090-0.233) indicates that there is considerable uncertainty in the model fit. In addition, the p_value = 0.007 indicates that the model does not fully fit the data. The Standardized Root Mean Square Residual (SRMR) of 0.063 falls below the recommended cutoff value (≤ 0.08), indicating that the model demonstrates a good level of fit, with relatively small discrepancies between the predicted and observed values.This indicates that the difference between the predicted and observed values is relatively small. A Goodness Fit Index (GFI) value of 0.995 indicates a very according to the good model. However, it is important to analyze the GFI Goodness Fit Index in conjunction with other indices for a comprehensive understanding of model fit. The McDonald Fit Index (MFI) value of 0.939 indicates that the model exhibits a good level of fit. According to the literature, an MFI value approaching 1.0 reflects a high degree of model fit with the empirical data. Thus, this finding reinforces the results indicated by the Goodness of Fit Index (GFI), leading to the conclusion that the estimated model adequately represents the structural relationships among the observed variables. The Expected Cross-Validation Index (ECVI) of 0.414 reflects the model's capacity for generalization, particularly in predicting patterns based on new data. A lower ECVI value indicates a better ability of the model to provide stable estimates that can be replicated across different samples. A lower value signifies a more effective model in prediction, and the current ECVI value suggests a fairly good predictive ability. Overall, although some measures such as SRMR, GFI, MFI, and ECVI show a satisfactory fit, the high RMSEA value indicates that the model still has shortcomings in its global fit. Overall, these findings suggest that although some measures of model fit, such as SRMR, GFI, MFI, and ECVI, provide positive indications, high RMSEA values indicate significant gaps in global fit. This underscores the importance of using multiple measures of fit simultaneously and emphasizes the need for further adjustments to achieve a more appropriate model. This study supports the literature, which emphasizes that comprehensive model evaluation requires broader considerations to ensure that the model can accurately describe the data at hand. Research by (Jackson et al., 2010) suggests that researchers should consider adjusting the model to improve the overall fit when a model shows some good measures of fit but still has RMSEA problems. This relates to the discovery that, despite demonstrating good fit in some measures, a high RMSEA still requires improvement.

3.5. Critical reasoning

The fifth indicator of critical reasoning consists of 10 items. The results of the confirmatory analysis are presented in the model plot as follows (Figure 5).

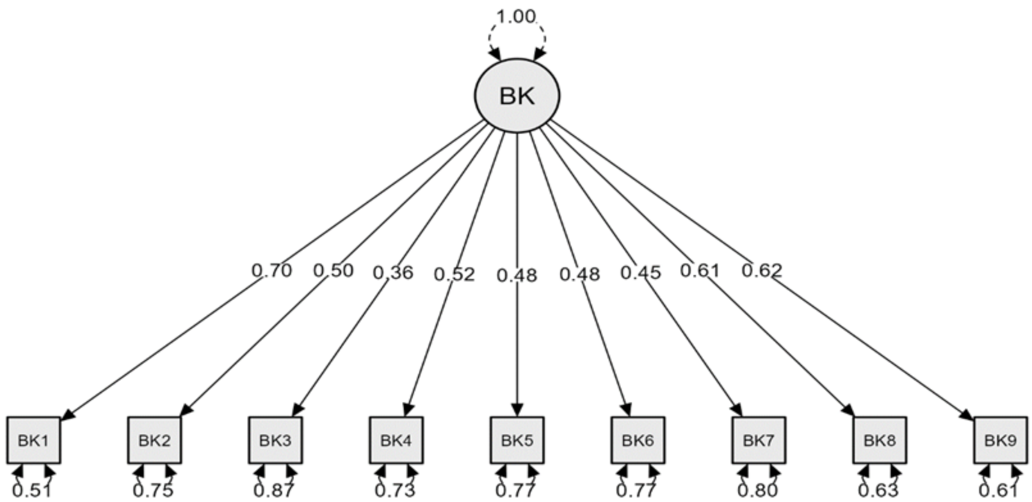

Figure 5 Critical reasoning variable construct.

The confirmatory factor analysis results reveal that the measurement item (BK1), "If I do not understand what the teacher explains in class, I always ask," is based on the factor loading coefficient. Overall, the research findings indicate that the measurement item BK1, which is titled "If I do not understand what the teacher explains in class, I always ask," highlights the importance of having a clear understanding of the teacher's provided material. This strengthens the evidence in the literature regarding the positive influence of teaching quality on students' critical thinking skills and emphasizes the need to focus on developing effective teaching strategies to support critical reasoning characteristic in elementary education settings. According to Wiggins & Tighe (2005), critical reasoning skills are crucial for students as they enable they to analyze data and make the right choices. The discovery that item BK3 made the largest contribution highlights the connection between teaching understanding and the development of students' ability to think critically.

The values of the Coeficient ω (Omega) = 0.769 and Coeficient α (Alpha) = 0.770 indicate that the measuring instrument used has very good internal consistency. A Coeficient ω (Omega) of 0.769 indicates that the instrument has strong reliability, with this value indicating that the items in the instrument are well correlated and consistent in measuring the intended construct. A Coeficient α (Alpha) of 0.770 also indicates excellent internal consistency, exceeding the ideal threshold of 0.70. This value indicates that the instrument provides stable and consistent measurements. Overall, these values indicate that the measurement instrument has excellent reliability. This instrument can be considered very reliable and effective in measuring the targeted variables with high consistency. Overall, the results showing that the coefficient ω (Omega) and coefficient α (Alpha) reached values above 0.70 indicate that the measurement instrument has very good reliability and high internal consistency. This finding not only strengthens the validity of the use of the instrument in the context of this study but also provides a strong basis for further research using the same measuring instrument, creating confidence in the results produced. This aligns with the research DeVellis et al. (2004), which suggests that the use of reliable and consistent measurement instruments is crucial for generating valid findings in social research. With high ω and α values, this instrument can be considered very effective in measuring the targeted variables, allowing researchers to produce more accurate results.

On The basis of the evaluation results with various fit indices, this model shows a fairly satisfactory fit, although it is still below the ideal standard. The Comparative Fit Index (CFI) value of 0.875 indicates a reasonably good model fit with the data, albeit not perfect. Studies by Neish & Wolf (2023) & Marsh & Alamer (2024) support that a CFI close to 0.90 is still acceptable, but a value above 0.90 is more desirable to ensure optimal model fit. The TLI of 0.834 also shows a fairly good fit, but this value is lower than the ideal standard of 0.90, indicating room for improvement in terms of model efficiency (Mueller & Hancock, 2018). The Tucker-Lewis Index (TLI) or Non-Normed Fit Index (NNFI) of 0.834 indicates that the model demonstrates an adequate level of fit. However, since the value remains below the ideal threshold (≥ 0.90), it suggests that the model is not yet fully optimal and requires further refinement to improve its overall fit. According to Bentler (1990) The Normed Fit Index (NFI) of 0.780 indicates a relatively low level of fit compared to other indices and falls below the expected standard, although it may still be considered within an acceptable range. The Relative Fit Index (RFI) of 0.707 further suggests that the model’s fit is not yet optimal and requires substantial improvement. Meanwhile, the Incremental Fit Index (IFI) of 0.881 approaches the ideal threshold (≥ 0.90), indicating that the model demonstrates a reasonably good level of fit, though it does not fully achieve the optimal criterion. Similarly, the Relative Noncentrality Index (RNI) of 0.875 reflects a moderately good fit, but there remains room for improvement to ensure that the model more adequately represents the data. Overall, this model shows a fairly adequate fit with the data, but some indices, such as TLI, NFI, and RFI, indicate that there is room for further improvement in order for the model to achieve an ideal fit. Fridman et al. (2016) sugested that model improvement can be accomplished through further exploration of the causal pathway or modification of parameters to increase the value of these indices. Overall, although several indices indicate an acceptable level of fit, the model still allows for improvement in order to achieve a more optimal alignment with the empirical data.

The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Sample-Size Adjusted BIC (SSABIC) values provide information about the complexity of the model and how well it predicts the data. The Following is an explanation of the function and interpretation of these values: The AIC, BIC, and SSABIC measure the balance between model compatibility and model complexity (number of parameters). These values penalize regarding the number of parameters used in the model to prevent overfitting (an overly complex model that may fit onli the existing data without generalizing well to new data). Lower values of AIC, BIC, and SSABIC indicate a better model because the model is more efficient in terms of fitting the data with fewer parameters. This means that the model has a better balance between complexity and fit. These Values can be used to compare models. When multiple models are compared, the model with a lower AIC, BIC, or SSABIC value is considered better because it provides a better fit to the data while using fewer parameters. Overall, AIC, BIC, and SSABIC values are useful tools for evaluating model quality, considering both fit and complexity, and selecting the optimal model on the basis of this balance. Overall, the use of AIC, BIC, and SSABIC in this study demonstrates a careful approach to evaluating model quality on the basis of the balance between fit and complexity.

The relevance of a study by Burnham et al. (2011) published in Model Selection and Multimodel Inference emphasizes the importance of the AIC and BIC in the model selection process. In this study, the authors explain how these two criteria help researchers select the right model by evaluating the balance between fit and complexity. This finding aligns with your study's explanation that the model with lower values of AIC, BIC, and SSABIC is deemed more effective. This finding reinforces the importance of these criteria in the optimal model selection process and highlights their relevance in the context of statistics and educational research. A study by Zürich et al. (2005) in the Journal of the Royal Statistical Society: Series B (Statistical Methodology) states that the use of the BIC in the context of statistical models can help avoid overfitting by imposing a greater penalty on more complex models. This finding supports the use of BIC in your study to maintain a balance between fit and complexity.

On the basis of the evaluation results with other fit measures, this model shows a fairly satisfactory fit overall. The Root Mean Square Error of Approximanition (RMSEA) is 0.088. This value indicates that the model has a satisfactory fit with the data, although it is slightl reater than the ideal threshold (0.06). The 90% confidence interval range (0.051-0.123) also shows considerable variationand the value of p = 0.047 indicates that although the model does not completely fit the data, its fit is still within acceptable limits. The Standardized Root Mean Square Residual (SRMR) of 0.066 falls below the recommended cutoff value (≤ 0.08), indicating that the model demonstrates a good level of fit, with relatively small discrepancies between the estimated and observed values. The Goodness Fit index (GFI) = 0.990, which indicates a decent model fit, approaching a perfect fit. However, the GFI results need to be considered in conjunction with other measures. The McDonald Fit Index (MF) value of 0.902 indicates a good fit, confirming the model's ability to accurately fit the data. The Expected Cross Validation Index (ECVI) value of 0.876 provides an indication of the model’s ability to predict new data. A lower ECVI value reflects a better capacity of the model to represent the population and enhances its potential for generalizability. In this case, a lower ECVI value indicates the model's superior predictive ability. Overall, although the RMSEA is slightly greater than the ideal threshold, other indicators such as SRMR, GFI, MFI, and ECVI indicate that the model has a satisfactory fit and is able to predict the data quite well. Overall, although the RMSEA is slightly greater than the ideal threshold, other measures, such as SRMR, GFI, MFI, and ECVI indicate that the model has a satisfactory fit and is able to predict the data quite well. Relevance to the study, An article by Beginner's Guide to Structural Equation Modeling explains that an RMSEA below 0.08 typically signifies an acceptable fit. Despite this study's slightly higher RMSEA, the p_value = 0.047 still suggests that the model falls within acceptable bounds. This is in line with the recommendation to assess models using multiple fit measures simultaneously.

his demonstrates the importance of a comprehensive approach in evaluating model fit and its impact on the development of measurement instruments in educational contexts. Clogg et al. (1995) published a study in Which Structural Equation Models were tested, which sugested that a model with a lower ECVI value has better predictive ability. This study's ECVI result of 0.876 suggests a good predictive ability for the model. This suggests that we can apply the model in a broader context, including the development of educational interventions. By including a Cartwright & Morgan (2021) article in the Journal of Educational Psychology we can develop more accurate measurement instruments in educational contexts by using a model with good fit. These findings indicate that the RMSEA value is slightly above the ideal threshold; however, when considered in conjunction with the other fit indices, the instrument can still be regarded as reliable for measuring the target variable in this study.

3.6. Creative

The sixth indicator of creative character encompasses seven elements. The results of the confirmatory analysis are presented in the model plot as follows (Figure 6).

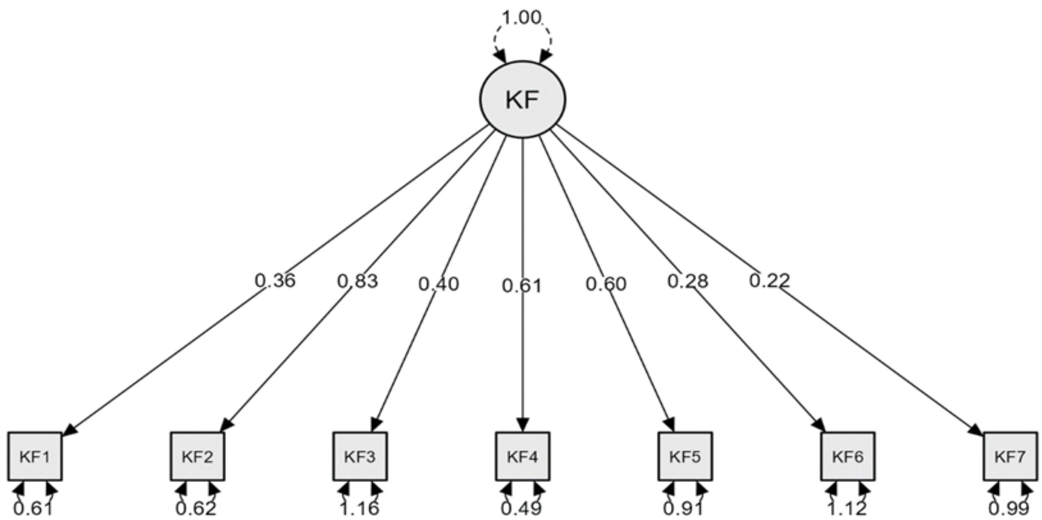

Figure 6 Creative variable construct.

According to the confirmatory factor analysis results, the factor loading coefficient indicates that the measurement item (KF4) is 'I like to imagine'. The research findings from the seven measurement items, item (KF4), or "I like to imagine," showed the greatest contribution to the creative character variable of students in elementary school. This finding indicates that students' adaptability is very important in the development of their creativity, which may be related to flexibility in thinking and the ability to face new challenges. This aligns with the research (Jaeger et al., 2012) . Which highlights the significant role of flexibility and adaptability in the development of creativity. Adaptable students are more creative because they can access different perspectives and solutions. The results of research by Amabile et al. (1996) showed that an environment that supports and allows students to adapt can increase creativity. In other words, external factors such as teacher and peer support also contribute to students' ability to adapt and innovate. Research by Lestari et al. (2024) emphasized the importance of character measurement in the educational context, where creative character can encourage better learning outcomes. Effective assessment of student characteristics, such as adaptability, can help educators develop more innovative teaching methods.

The values of the Coeficient ω (Omega) = 0.628 and Coeficient α (Alpha) = 0.648 indicate that the measuring instrument used has adequate internal consistency but is not very high. A Coeficient ω (Omega) of 0.628 indicates that the instrument has sufficient reliability, although this value is slightly below the ideal threshold of 0.70. This finding indicates that the items in the instrument have adequate correlation, but there is room for improvement in terms of consistency. A Coeficient α (Alpha) of 0.648 also indicates adequate internal consistency but does not reach a very good level. The instrument may require improvement to enhance stability and consistency in its measurement, as this value falls below the 0.70 threshold. Overall, these values indicate that the measurement instrument has sufficient reliability, but there is potential for improvement. While the instrument remains usable, it might require enhancements to its items or structure to increase internal consistency and overall reliability. The results of the analysis above have been studied by Tavakol et al. (2011) in their article in Medical

Education, who showed that coefficient α value below 0.70 can affect the construct validity of the measurement instrument. They emphasize the importance of ensuring that the instrument not only has sufficient reliability but also must be able to reflect the intended construct.

The Chi-square test results, which were used to compare the baseline model and the factor model, are as follows: the baseline model has a Chi-square (X^2) value of 111,700 with 21 degrees of freedom (df). The factor model has a Chi-square (X^2) value of 18,244 with 14 degrees of freedom (df) and a p_value of 0.196. The p_value of 0.196, which is greater than 0.05, indicates that there is no significant difference between the factor model and the data. In other words, the factor model does not show a poor fit to the data. This means that the factor model can be considered to fit the existing data because a higher p_value indicates that the difference between the proposed model and the data is not statistically significant. Overall, the findings indicate that the factor model shows adequate fit with the data, which does not exhibit significant fit issues. This suggests that we can accept the factor model as a suitable representation of the current data. Overall, the Chi-square test results indicate that the factor model has an adequate fit with the data providing a strong basis for using the model in further analysis. This emphasizes the importance of assessing model fit not only through Chi-square test but also by considering additional fit measures to obtain a more holistic picture of the quality of the model. For example, research by Hair et al. (2019) in the book Principles and Practice of Structural Equation Modeling explains that a p_a higher value than 0.05 in the Chi-square analysis indicates that the proposed model does not have significant fit problems. These results support the acceptance of the factor model as an appropriate representation of the empirical data.

The model fit index evaluation results indicate a very good overall fit for this model, although some aspects still require improvement. Each Index is Described as follows: Compartive Fit Index (CFI)=0.953. This value is close to the ideal threshold (0.95), which indicates that the model has a fantastic fit with the data. The Tucker-Lewis Index (TLI) or Non-Normed Fit Index (NNFI) of 0.930, although slightly below the ideal threshold (≥ 0.95), indicates a satisfactory level of model fit and can be considered close to the optimal standard. The Normed Fit Index (NFI) = 0.837, indicating a fairly good model fit. However, it falls slightly short of the ideal value of 0.90, suggesting that the model still has room for improvement. The Relative Fit Index (RFI) of 0.755 suggests that the model's fit is less than optimal compared to other indices, though it remains within an acceptable range. In contrast, the Incremental Fit Index (IFI) of 0.957, which exceeds the recommended threshold of 0.95, indicates an excellent level of fit between the model and the data. Similarly, the Relative Noncentrality Index (RNI) of 0.953, consistent with the CFI and IFI values, also demonstrates that the model provides an excellent representation of the observed data. Overall, this model has a fantastic fit, especially in terms of the CFI, IFI, and RNI values. Although several indices, such as NFI and RFI, are still below the ideal standard, the overall model fit is considered quite good.Overall, the research findings on model fit clearly show that, despite the model's good results, there is still room for improvement in certain indices such as NFI and RFI. Correlation A study by Hu & Bentler (1999) in Principles and Practice of Structural Equation Modeling showed that a CFI value above 0.95 indicates excellent model fit. Kline also emphasizes the importance of examining various fit indices to obtain a more complete picture of the quality of the model. The research findings on high CFI values strengthen the results of the research. These findings reinforce the validity of the research results and offer further insight into the significance of conducting a thorough analysis of various fit indices in statistical models.

The Akaike Information criterioan (AIC), Bayesian Information Criterion (BIC), andSample-Sixe Adjusted BIC (SSABIC) values provide important information about the complexity of a model and how well it predicts the data. We use these values to evaluate and compare the models as follows: the AIC, BIC, and SSABIC measure the balance between model fit and complexity. They penalize the number of parameters in the model to avoid overfitting (where the model is too complex and only fits the existing data without being reliable for new data). Lower values of AIC, BIC, and SSABIC indicate a model that is better at this balance. This means that the model provides a satisfactory fit to the data while using fewer parameters. People generally prefer simpler models with lower values because they are more efficient and easier to interpret. Thjese Values can be used to compare different models. When multiple models, are compared, a model with lower AIC, BIC, or SSABIC values is considered better because it is more efficient in terms of data fit and model complexity. Overall, the AIC, BIC, and SSABIC are useful tools for evaluating and selecting the best model on the basis of balance between fit and complexity. Models that score lower on these criteria tend to be better at predicting new data and are more efficient in terms of parameter usage. Overall, the research findings involving AIC, BIC, and SSABIC indicate that the proposed models have a satisfactory balance between fit and complexity.

The study by Hair et al., (2019) who first introduced the AIC, emphasized that a lower AIC value indicates a better model in terms of the balance between fit and complexity. This study's use of the AIC in the evaluation aligns with the widely recognized principle in the literature. The study by Srivastava et al. (2005) introduced the BIC as an alternative to the AIC and emphasized that it imposes a greater penalty on models with a larger number of parametersIn the journal article Statistical Planning and Inference, this study highlighted that BIC is more suitable when large datasets are used. The research findings showing the use of the BIC for model selection are in line with this recommendation (Sugiura et al., 1978). Who discussed SSABIC, and stated that SSABIC offers advantages in situations where sample sizes are small and models are complex. Using SSABIC demonstrates a proper understanding of the importance of adjusting the penalty for sample size. Your research reflects the approach suggested in the literature on model evaluation. A study by Burnham et al. (2011) in Model Selection and

Multimodel Inference emphasized that models with lower AIC, BIC, and SSABIC values not only have better fit but are also more efficient in parameter utilization. Research findings reflecting this principle support their recommendation and highlight the importance of selecting efficient models.

On the basis of the measurement results obtained via other fit measures, this model has a very good fit with the data. Each Measure is decribed: Root Mean Squre Error of Approximation (RMSEA)= 0.050. This value indicates that the model has a good fit with the data because it is below the ideal threshold of 0.06. The 90% confidence interval range (0.000-0.107) shows the variation that allows for a good fit. This is in line with the findings of several previous studies showing that RMSEA below 0.06 can be relied upon to measure the fit of a structural model. The model significantly fits the data, as indicated by the p_value of 0.452, which is greater than 0.05. The SRMR (standardized root mean square residual) value is 0.054. This value also shows a very good fit because it is below the threshold of 0.08, which indicates that the difference between the predicted and observed values is relatively small according to the standard. The Goodness of Fit Index (GFI) value of 0.995 indicates that the estimated model demonstrates an excellent fit with the empirical data. This value approaches the ideal score of 1.0, which theoretically represents a perfect fit. Therefore, it can be concluded that the model is highly capable of explaining the structural relationships among variables and is consistent with the observed data patterns.

The McDonald Fit Index (MFI) of 0.983 indicates a very good model fit, in line with the documented principles of model fit in research, which are supported by the results of the GFI and SRMR. The Expected Cross Validation Index (ECVI) = 0.498: This value indicates the the model's ability to make predictions based on new data. The model's predictive ability improves with a lower ECVI value, and this value suggests that the model has a fairly good predictive ability. Overall, this model shows a decent fit to the data, with the RMSEA, SRMR, GFI, and MFI indicators all indicating an optimal fit. We expect the model to have good predictive performance with a low ECVI. Overall, the research findings show that the model has a very good fit to the data, with all indicators such as RMSEA, SRMR, GFI, and MFI showing optimal results Zyphur et al. (2023), indicating that an RMSEA value below 0.06 is considered an indicator of a very good model fit. The research findings showing RMSEA = 0.050 are consistent with this recommendation and strengthen the validity of the model. The linkage to studies published in Scopus journals strengthens the validity of the research results and highlighting the importance of conducting a thorough analysis of various fit measures in statistical model evaluation. These findings not only provide a clear picture of model fit but also emphasize the potential for use in broader research applications.

4. Conclusion

The study, which used the confirmatory factor analysis method to measure the Profile of Pancasila students in elementary school, concluded that the critical reasoning, religion, and independent dimensions have good reliability, where the mutual cooperation, global diversity, and creative dimensions have adequate reliability but still require improvement. Model fit shows that the creative and religious dimensions have very good model fit, where the critical reasoning dimension has a fairly good model fit but still needs improvement. On the other hand, the Mutual Cooperation, Global diversity, and Independt dimensions show poor model fit and require revision to improve their suitability. The creative and critical reasoning models work better and fit the data better than the other dimensions do, according to the information criteria (AIC, BIC, and SSABIC). This means that these variables are better at predicting the personality of the Pancasila Student Profil in elementary schools. Overall, the implementation of the Pancasila Student Profil in elementary schools has gone well in several dimensions, but there is still room for improvement, especially in the dimensions of mutual cooperation and global diversity. Therefore, we must develop a measurement instrument and recommend a wider sample for further research.

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Ethical Considerations

This study was conducted in accordance with the principles of research ethics, including voluntary informed consent, maintaining data confidentiality and anonymity, and ensuring that data is used only for research purposes. There were no conflicts of interest that could affect objectivity, and research funding did not influence the design or results . This study has also been approved by the relevant ethics committee.

Conflict of Interest

The author declare that there is no potential conflict of interest.

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