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SHOULD LIKERT DATA BE TRANSFORMED USING SUMMATED RATING SCALE? A CONFIRMATORY FACTOR ANALYSIS STUDY ON THE CONTINUOUS LEARNING

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Abstract

Continuous Learning competence can be measured through self-assessment to minimize interview failure. The problem arises when the Continuous Learning instrument is developed using a Likert Scale. Can the data from the distribution of the instrument be used directly, or must it be converted using the summated rating scale approach? This study aims to compare the results of instrument analysis through Confirmatory Factor Analysis (CFA) based on direct data and conversion data. The method used is descriptive quantitative, involving 281 undergraduate students in Indonesia. Instrument analysis includes estimating reliability, convergent validity, and construct validity through CFA. The study's results show that the reliability and convergent validity of the data converted using the summated rating scale are higher than those of the direct data. However, the direct data produces a better measurement model fit test value compared to the converted data. However, the difference in value between the two types of data is very small and does not have any meaningful difference. Therefore, the data from the instrument can be directly analyzed without converting to the summated rating scale. This study provides insights to researchers and academics in developing a continuous learning instrument. Additionally, it offers insight into how processing Likert data on the Continuous Learning instrument is very straightforward and does not require data conversion through a summated rating scale.

Keywords: Likert data, Continuous learning, Summated rating scale, Confirmatory factor analysis

INTRODUCTION

The world today is experiencing such rapid and dynamic development, especially in the development of increasingly sophisticated technology. With this development, it is not surprising that the role of humans will be replaced by advanced technology, becoming a threat in the future. Therefore, to survive amid massive change, humans must be able to adapt and innovate to compete globally. The skills still used today may no longer be needed in the future because they are no longer relevant to the demands of that time. Therefore, continuously adapting and learning new things is essential for the current generation.

Learning new things is not only beneficial professionally but also enriches personal life. The more you know about new things, the broader the perspective you get. The above concept is a reflection of self-development called Continuous Learning. Continuous Learning is the constant learning process of acquiring new knowledge and skills (Toquero, 2020). This process will help a person to continue to grow, both in the personal and professional realms. Continuous learning is acquiring deeper and broader knowledge and skills regularly and directly and applying them to new behaviors. At the individual level,

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this includes learning new disciplines, expanding knowledge and expertise, and reconstructing self-concept. Continuous learning is a routine mindset and behavior that reflects belief and dedication to learning and change (Sessa & London, 2015). Through Continuous Learning, hidden potentials within oneself can be identified, and new opportunities for future success can be found.

Continuous learning competence has become an exciting concern for HR heads when recruiting employees. Not only in the industrial world, but educational institutions also often consider this ability one of the soft skills that educators must possess. Someone with good Continuous Learning competence will quickly adapt and develop to innovate and face future challenges (Mlambo et al., 2021). Therefore, at every moment of job or scholarship recruitment, Continuous Learning becomes one of the competencies explored by the organizers.

Students should be aware of the importance of continuous learning competence from the beginning. So far, Continuous Learning competence has been explored through job recruitment interviews, further studies, or professions. Most students only realize the importance of Continuous Learning competence at that time. As a result, the interviews conducted did not go well. This can be anticipated from the beginning so that students can prepare themselves long before entering the workforce.

A tool is needed to detect continuous learning competence and measure this competence accurately. However, until now, Continuous Learning competence has only been measured through interviews, which is not practical. Therefore, developing a useful and efficient Continuous Learning instrument is a necessity. One possible thing to develop is to create an instrument in the form of self-assessment to measure Continuous Learning competence.

The Continuous Learning competence developed in this study is based on four key indicator aspects: self-need, self-development, implementation, and risk-taking behavior (PPG Team, 2022). The *self-need* aspect refers to an individual's awareness of their personal and professional need to continuously learn and develop in order to stay relevant in the face of dynamic changes. *Self-development* reflects the individual's ability to take concrete steps to meet these learning needs through planning, goal setting, and dedication to self-improvement. The *implementation* aspect measures how well a person can apply the knowledge and skills they have acquired in real-life situations, whether at work, in education, or in everyday life, thus turning learning into practical, actionable outcomes. Finally, *risk-taking behavior* indicates an individual's willingness to take risks and face uncertainty in the learning and development process, often involving the courage to try new things and learn from failure.

In this study, the development of an instrument to assess these four aspects focuses on ensuring construct validity through *Confirmatory Factor Analysis* (CFA), which aims to verify that the instrument accurately measures the dimensions of Continuous Learning competence as intended. Additionally, the instrument's reliability is estimated to ensure consistency in measurement. By doing so, the developed instrument is expected to serve as a valid and reliable tool for assessing Continuous Learning competence in various contexts, including education and human resource development.

The Continuous Learning instrument uses a Likert Scale to produce ordinal data (Jamieson, 2022; Zikmund, 2000). Meanwhile, the required data is at least an interval scale to perform parametric statistical analysis. In this case, there is a debate among experts (Sullivan dan Artino, 2013) that data obtained from the Likert Scale cannot be considered interval data (Simamora, 2022), so it must first be converted using a summated rating scale (Kampen, 2019) so that the data can be continued for analysis to CFA. However, another opinion says that ordinal data obtained from the Likert Scale can be considered as if it were interval scale data. To perform CFA analysis, it is unnecessary to convert the data (Cheng et al., 2021; Kam, 2020). Based on this debate, the authors are interested in analyzing the fit model on the construct of the Continuous Learning instrument based on the direct data obtained from the instrument and the data converted through the summated rating scale. The CFA results of the two data types will be compared to see if there is a difference in the fit model from the analysis.

This study aims to explore this debate by comparing the fit model results of CFA using both raw Likert scale data and data converted through a summated rating scale. By doing so, it seeks to determine whether there is a significant difference in the fit model based on the type of data used.

METHODOLOGY

This study employed a quantitative approach with descriptive analysis to explore the construct validity and reliability of a Continuous Learning self-assessment instrument. The research involved 281 undergraduate students from various regions of Indonesia, including Sumatra, Java, NTT (East Nusa Tenggara), and Papua, as respondents. Data were collected using a self-administered questionnaire designed to measure Continuous Learning competence based on a Likert Scale with five response options: strongly disagree (SD), disagree (D), hesitant (H), agree (A), and strongly agree (SA). The five-point Likert scale was chosen as it offers balanced response options while maintaining clear distinctions between adjacent choices, making it more effective for capturing nuanced opinions compared to scales with fewer or more points (Joshi et al., 2015; Mumu et al., 2022).

The Continuous Learning instrument consists of 15 items, developed based on four key indicator aspects: (1) *self-need* (items 1–3), which assesses an individual's awareness of their need for continuous learning; (2) *self-development* (items 4–9), which evaluates their commitment to self-improvement; (3) *implementation* (items 10–12), which measures the application of newly acquired knowledge and skills in practice; and (4) *risk-taking behavior* (items 13–15), which looks at the individual's willingness to take risks and engage in new learning experiences. Each of these aspects plays a significant role in defining a person's continuous learning competence.

Upon distributing the questionnaire, two types of data were produced: (1) *Direct data* (Label A), which refers to the raw data obtained directly from the respondents' answers to the questionnaire, and (2) *Conversion data* (Label B), where the original responses were transformed using the summated rating scale approach to address potential concerns about the ordinal nature of Likert scale data in parametric analysis.

Table 1. Description of Data Types

Type of Data	Label	Description
Direct data	A	Data obtained directly from the distribution of Continuous Learning instruments
Conversion data	B	Converted data using the summated rating scale

Both types of data were analyzed using Confirmatory Factor Analysis (CFA) to evaluate the model fit, construct validity, and reliability of the Continuous Learning instrument. The CFA assesses how well the measurement items reflect the underlying theoretical constructs. Following this, a t-test was conducted to compare the factor loading values between the two datasets (Direct data vs. Conversion data). This

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comparison aims to determine whether any significant differences exist between the two datasets, which would provide insights into the appropriateness of using untransformed Likert scale data in confirmatory factor analyses (Safitri, Chastanti, et al., 2022; Safitri, Muti'ah, et al., 2022). The results of these analyses will inform researchers on the most suitable method for handling Likert scale data in future studies, specifically regarding whether to use raw or transformed data in CFA and other statistical analyses.

FINDINGS

Proving The Construct Validity

The first step in developing an instrument is to determine its construct. In this study, construct validity was carried out through Confirmatory Factor Analysis (CFA) to confirm that the items developed were the indicators of Continuous Learning competence set by the theory. CFA analysis obtained the loading factor estimation values for each item as follows.

Table 2. Loading Factor Estimation Value of Continuous Learning Instrument

Factor	Indicator	Estimate		Std. Est. (all)		Conclusion
		A	B	A	B	
Self-Need	SN1	0.232	0.438	0.386	0.410	Invalid
	SN2	0.404	0.413	0.592	0.605	Valid
	SN3	-0.136	-0.047	-0.128	-0.069	Invalid
Self-Development	SD1	0.494	0.494	0.665	0.665	Valid
	SD2	0.543	0.543	0.664	0.665	Valid
	SD3	0.351	0.636	0.622	0.622	Valid
	SD4	0.410	0.406	0.624	0.618	Valid
	SD5	0.563	0.562	0.656	0.654	Valid
	SD6	0.425	0.425	0.607	0.607	Valid
Implementation	Im1	0.459	0.455	0.655	0.649	Valid
	Im2	0.320	0.579	0.578	0.602	Valid
	Im3	0.401	0.401	0.522	0.521	Valid
Risk Taking Behavior	RTB1	0.570	0.678	0.706	0.676	Valid
	RTB2	0.684	0.678	0.838	0.830	Valid
	RTB3	0.727	0.734	0.864	0.872	Valid

The standardized estimation value can show the loading factor estimation value of the Continuous Learning instrument items. Based on the CFA results in Table 2, it is known that these 15 items have a factor loading value between -0.128 to 0.864 for direct data (A) and -0.069 to 0.872 for conversion data (B). According to theory, the critical factor loading value for each item to be declared valid is more significant than 0.5 (Hair et al., 2019: 663). Referring to Table 2, 13 items were declared valid, and two were declared invalid for both data types. The invalid items are part of the Self-Need indicator aspect, namely items 1 and 3. These invalid items apply to the same items in both direct and conversion data.

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Fit of Measurement Model

The most important thing to note in proving construct validity is the fit of the measurement model. The measurement model fit index refers to the statistics used to evaluate the extent to which the measurement model represents the relationship between the observed variables and the underlying latent variables. Based on the CFA results, the fit statistic values were obtained, which will then be compared with the model fit threshold value to evaluate the overall model fit. Some commonly used goodness of fit indices recommended by experts are presented in Table 3.

The Table 3 presents the fit criteria for the model, comparing A-Value and B-Value against established thresholds to assess the overall model fit. Based on the analysis, both A-Value and B-Value demonstrate a good fit across most criteria. For the P-Value, the threshold of greater than 0.05 was not met as both A-Value and B-Value were below 0.001, indicating a significant model fit for both datasets. In terms of RMSEA and SRMR, both A-Value (0.064, 0.045) and B-Value (0.069, 0.047) were within the acceptable range of ≤ 0.08, confirming a good fit. The GFI exceeded the threshold of ≥ 0.90 for both A-Value (0.996) and B-Value (0.986), demonstrating an excellent fit. Similarly, CFI and IFI values also met the required threshold of ≥ 0.90, with A-Value (0.929, 0.930) and B-Value (0.919, 0.920) confirming a strong fit. The PNFI was also above the minimum threshold of ≥ 0.50 for both A-Value (0.702) and B-Value (0.695), indicating a good fit. However, for NNFI, while A-Value (0.911) exceeded the threshold of ≥ 0.90, B-Value (0.899) fell slightly below, suggesting a marginally acceptable fit. Lastly, for RFI, both A-Value (0.847) and B-Value (0.835) did not meet the threshold of ≥ 0.91, indicating that this criterion was not fully achieved. Despite the minor shortfall in NNFI and RFI, the model fit across most criteria is satisfactory, demonstrating that the model is robust, although slight improvements may be necessary in certain areas.

Table 3. Results of Model Fit Test Using CFA

Criteria of Model Fit	Threshold	A-Value	B-Value	Conclusion
P-Value	> 0,05	<0,001	<0,001	Fit
RMSEA	≤ 0,08	0.064	0.069	Fit
Standardized root-mean-square residual (SRMR)	≤ 0,08	0.045	0.047	Fit
Goodness of fit index (GFI)	≥ 0,90	0.996	0.986	Fit
Comparative Fit Index (CFI)	≥ 0,90	0.929	0.919	Fit
Bollen's Incremental Fit Index (IFI)	≥ 0,90	0.930	0.920	Fit
Parsimony Normed Fit Index (PNFI)	≥ 0,50	0.702	0.695	Fit
Bentler-Bonett Non-normed Fit Index (NNFI)	≥ 0,90	0.911	0.899	Fit
Bollen's Relative Fit Index (RFI)	≥ 0,91	0.847	0.835	Fit

Next, to determine the significance of the influence between variables, an analysis was conducted by examining the factor loadings of the impact of aspects such as Self-Need, Self-Development, Implementation, and Risk-Taking Behavior on each item. After performing the JASP analysis, the output was obtained in Figure 1 for the direct data (A) and Figure 2 for the converted data (B).

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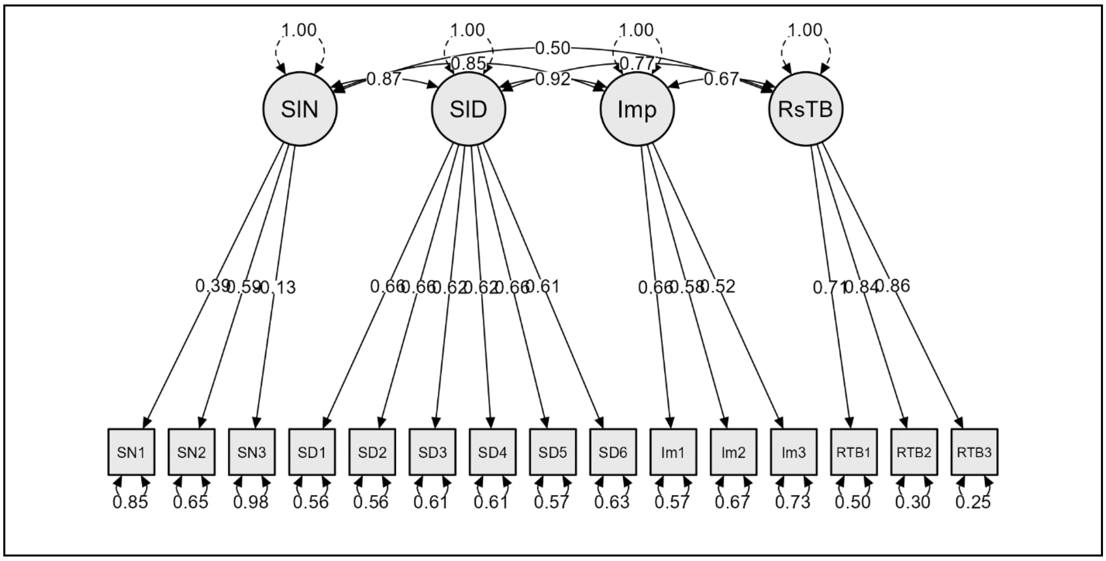

Figure 1. The Plot of Construct Validity Continuous Learning (Direct Data)

The image shows a structural equation model (SEM) diagram, which represents the relationships between four latent variables: SIN (Self-Need), SID (Self-Development), Imp (Implementation), and RsTB (Risk-Taking Behavior). Each of these latent variables has observable indicators (items) associated with them. For example, SIN is measured by items SN1 through SN3, while SID is measured by items SD1 through SD6, and so on. The standardized factor loadings for each indicator are displayed, indicating the strength of the relationship between each latent variable and its respective observed variables.

Self-Need (SIN) is associated with three indicators (SN1, SN2, and SN3) with factor loadings of 0.85, 0.65, and 0.98 respectively, showing strong relationships between the latent variable and the indicators. Self-Development (SID) is measured by six items (SD1 to SD6), with factor loadings ranging from 0.53 to 0.67, reflecting moderate to strong relationships with this latent construct. Implementation (Imp), measured by three indicators (Im1, Im2, and Im3), has loadings between 0.57 and 0.73, indicating strong associations. Risk-Taking Behavior (RsTB), on the other hand, is measured by three indicators (RTB1, RTB2, and RTB3) with varying loadings of 0.70, 0.30, and 0.25, reflecting that RTB3 has a weaker association with the latent variable.

The correlations between the latent variables are indicated with values such as 0.85 between SIN and SID, 0.50 between SID and Imp, and 0.67 between Imp and RsTB, suggesting positive relationships between these constructs. The diagram also shows direct and indirect relationships, with arrows representing the direction of influence among the variables. Overall, the model attempts to validate the measurement structure of these four key aspects of continuous learning competence, with factor loadings and correlations suggesting varying degrees of influence between the indicators and latent variables. This visualization is crucial for assessing the validity of the continuous learning construct and its components.

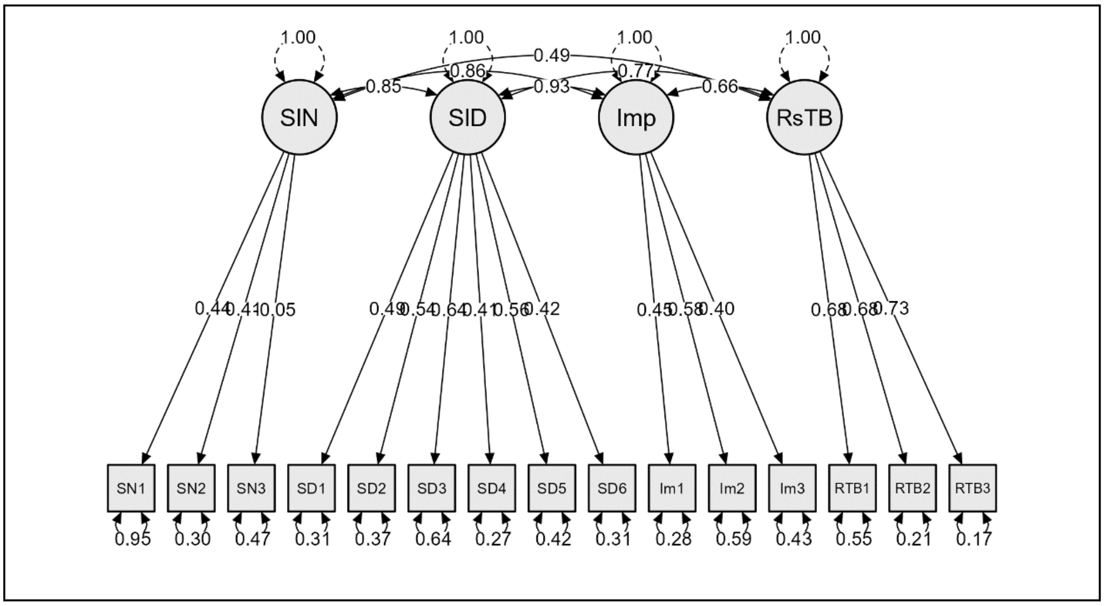

Figure 2. The Plot of Construct Validity Continuous Learning (Conversion Data)

The image presents a structural equation model (SEM) diagram representing the construct validity of Continuous Learning based on conversion data. The model includes four latent variables: SIN (Self-Need), SID (Self-Development), Imp (Implementation), and RsTB (Risk-Taking Behavior). Each latent variable is measured by a set of observable indicators with factor loadings reflecting their relationship strength (Istiqlal et al., 2024; Safitri et al., 2024; Safitri & Ansyari, 2024).

Self-Need (SIN) is linked to three indicators (SN1, SN2, and SN3) with standardized factor loadings of 0.95, 0.31, and 0.37, respectively. These values suggest that SN1 has a much stronger association with the SIN construct than SN2 and SN3. Self-Development (SID) is measured by six indicators (SD1 to SD6) with loadings ranging from 0.42 to 0.64, indicating moderate associations. The strongest relationships for SID are with SD3 (0.64) and SD4 (0.62), while SD5 (0.42) shows a weaker connection.

Implementation (Imp) is measured by three indicators (Im1, Im2, and Im3), with factor loadings ranging from 0.28 to 0.55. Im2 shows the strongest association (0.55), while Im1 has the weakest (0.28). Risk-Taking Behavior (RsTB) is associated with three indicators (RTB1, RTB2, and RTB3) with loadings of 0.55, 0.21, and 0.17, respectively. This indicates that RTB1 has the strongest connection to the RsTB construct, while RTB3 shows a significantly weaker association.

Additionally, the model includes correlations between the latent variables: 0.85 between SIN and SID, 0.49 between SID and Imp, 0.66 between Imp and RsTB, and 0.60 between RsTB and SIN. These correlations suggest positive relationships between the latent variables, with varying strengths. The strongest correlation exists between SIN and SID, indicating that these two constructs are closely related, while the weakest is between SID and Imp. In summary, this diagram visualizes the measurement structure of continuous learning competencies, showing varying degrees of influence between indicators and latent variables, along with correlations among the latent constructs. The conversion data provides insights into how each indicator contributes to its corresponding latent variable and how the latent variables interrelate.

After it is known that the model fits, the following analysis examines the standard factor loading value of each indicator or dimension. The analysis results show that a standard factor loading value ≥ 0.40 can be declared valid. From the output in Figures 1 and 2, it is known that there are 14 items on four indicators that have a factor loading greater than 0.40. There is 1 item on the Self Need indicator with a factor loading < 0.4, namely item 3, with a factor loading of 0.13 for direct data and 0.05 for conversion data. Thus, it can be said that the four indicators, namely Self-Need, Self-Development, Implementation, and Risk-Taking Behavior, are valid for describing the Continuous Learning model. Therefore, it can be concluded that these 14 items are valid for measuring the indicator.

Estimating of Reliability and AVE

After the items on the Continuous Learning instrument are declared valid through factor analysis, the next step is to estimate the convergence reliability and validity. Reliability is a series of measurements with consistent results if distributed at different times and places. Reliability is a series of measurements or measuring instruments that have consistency when the measurement is carried out repeatedly (Azwar, 2012, 2022; Retnawati, 2017). In this study, the reliability of direct data (A) on the Continuous Learning instrument was 0.843, while for conversion data (B), the resulting reliability was 0.859. Based on this data, it can be stated that the Continuous Learning instrument is highly reliable.

After estimating the instrument's reliability, the convergent validity is proved by calculating the Average Variance Extracted (AVE) value. Convergent validity aims to determine the validity of each relationship between the indicator and the construct or latent variable (Amora, 2021; Anis et al., 2020). This representation can be demonstrated through unidimensionality and expressed using the Average Variance Extracted (AVE) value. This study's convergent validity results of direct data (A) and conversion data (B) are as follows.

Table 4. Comparison of Average Variance Extracted (AVE) Value

Factor	AVE (A)	AVE (B)	Difference (B-A)
Self-Need	0,121	0,175	0,054
Self-Development	0,415	0,409	-0,006
Implementation	0,341	0,350	0,009
Risk Taking Behavior	0,652	0,612	-0,040

The data above shows that the lowest AVE value is in the Self-Need indicator, and the highest is in the Risk-Taking Behavior indicator. According to theory, the AVE value should be at least 0.5. This value illustrates that adequate convergent validity means that one latent variable can explain more than half of the variance of its indicators on average (Ghozali, 2016). In the data above, the Risk-Taking Behavior indicator has an AVE value > 0.5, which is 0.652 (A) and 0.612 (B). This means this indicator has a high value and meets the convergent validity. Meanwhile, the Self-Need, Self-Development, and Implementation indicators have an AVE value < 0.5 in both data types, meaning these three indicators have low convergent validity.

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DISCUSSION

The purpose of this study is to compare the results of the analysis of the Continuous Learning instrument from direct data and data converted through the summated rating scale. Based on the results of Confirmatory Factor Analysis (CFA), the difference in the estimated factor loading value of the Continuous Learning instrument on direct data and conversion data is 0.01 to 0.06. There are 6 out of 15 items have a difference in factor loading value of 0, 5 items of conversion data > direct data, and four items of conversion data < direct data. With the minimal difference in factor loading values in the two types of data and the inconsistency of the difference in each item, it can be concluded that there is no difference between the two types of data. Table 1 also shows two invalid items in items 1 and 2 in both data types. The following is a descriptive statistic of the factor loading in the two data types to reinforce this statement.

Table 5. Descriptive Statistics of Factor Loading on Data A And B

	Group	N	Mean	SD	SE	Coefficient of variation
CL	A	15	0.430	0.205	0.053	0.477
	B	15	0.493	0.186	0.048	0.377

The data in Table 5 show that the mean, standard deviation, standard error, and covariance of the converted data's factor loading are better than the direct data, although the differences are minimal. A t-test was conducted to examine the differences between the two data sets and determine whether these differences are significant. The following are the results of the t-test.

Table 6. Independent Samples T-Test

	t	df	p	Cohen's d	SE Cohen's d
Continuous Learning	-0.884	28	0.384	-0.323	0.370

Note. Student's t-test.

The results of the independent samples' T-test analysis in Table 6 show that the p-value is 0.384. According to the theory, if the resulting p-value is more significant than the significance level, there is no difference between the two data sets (Delacre et al., 2021). This study's significance level is 0.05, making the p-value > 0.05. Therefore, it can be concluded that there is no difference in factor loading values between the direct data and the converted data.

Furthermore, in the results of the model fit test using CFA, it is seen that both the direct data and the converted data fit all the criteria for the measurement model. Upon closer inspection, the difference in values between the direct and converted data is minimal, ranging from 0.002 to 0.012. Overall, the model fit values for the data obtained directly from the Continuous Learning instrument are better than those converted through the summated rating scale (Di et al., 2022; Prabaningtias, 2022). This contrasts with the factor loading comparison results, which show no difference between the two data types.

In the results of the reliability estimates for both data sets, there is a slight difference in reliability between the direct data and the converted data, with a difference of 0.016. Similarly, for convergent validity, the difference in AVE values between the two data sets ranges from 0.006 to 0.054 across the four aspects of Continuous Learning. In the Continuous Learning instrument's reliability and concurrent validity analysis, the converted data overall shows higher values than the direct data. This indicates that data converted through the summated rating scale is more stable, resulting in better statistical analysis values (Ismail et al., 2021).

Based on the discussion above, it can be concluded that data obtained directly from the Continuous Learning instrument will yield better values for the model fit test compared to data converted using the summated rating scale. Conversely, data converted through the summated rating scale will provide higher reliability and convergent validity than data obtained directly from the questionnaire distribution. However, both types of data yield the same factor loading values in the construct validity of the Continuous Learning instrument. Researchers should differentiate between Likert scales and Likert-type items when analyzing and interpreting data. Likert-type items using Likert response options should be descriptively analyzed using frequencies, modes, and medians. On the other hand, Likert scales, composed of multiple Likert-type items, can be interpreted descriptively by developing a scale of class intervals from the composite scores. This involves using a one-sample t-test and calculating the relative importance index (Alkharusi, 2023; Kislyonkova & Lebedeva, 2022).

CONCLUSION

Based on the discussion above, it can be concluded that the data obtained directly from the Continuous Learning instrument will produce better values for the measurement model fit test compared to data converted using the summated rating scale. Furthermore, data converted through the summated rating scale will provide higher reliability and convergent validity than data obtained directly from the questionnaire distribution. However, both types of data produce the exact factor loading values on the construct validity of the Continuous Learning instrument.

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