An-Najah University Journal for Research – B
Humanities

مجلـــة جامعـــة النجـــاح للأبحــــــاث - ب
العلوم الإنسانية

Estimating the Validity and Reliability of the Metacognitive Thinking Scale Considering Missing Data Proportions and Imputation Methods

Basel Khamis Salem Abu-Foudeh

Received: 26th Feb. 2024, Accepted: 7th Jan. 2025, Published: ××××, DOI:××××

Accepted Manuscript, In press

Abstract: Aim: The study aimed to estimate the validity and reliability of the metacognitive thinking scale considering missing data proportions and imputation methods. To achieve the objectives of the study, a metacognitive thinking scale (42 items) was administered to a randomly selected sample of 382 undergraduates from the Arab Open University in Jordan over the course of the 2023-2024 academic year. **Methodology**: The study used descriptive and analytical methods. **Results**: The results of the exploratory factor analysis indicated that the cumulative explained variance values using the logarithm of the Expectation Maximization (EM) method were higher compared to the reference group, while the cumulative explained variance values decreased using the series mean method (SM). The values of the Cronbach Alpha reliability coefficients and the McDonald Omega reliability coefficients showed differences in favor of the Logarithm of Expectation Maximization (EM) method for all cases of missing data proportions compared to the reference group, while the differences were in favor of the reference group compared to the Series Mean method (SM). **Conclusions:** The Expectation Maximization (EM) logarithm method is superior to other methods for imputation of missing data. **Recommendation:** The possibility of using the logarithm of the Expectation Maximization Method (EM) for imputing missing data. It is also conducting a comparative study that takes into account varying proportions of missing data and different imputation methods using psychological scales.

Keywords: Validity; Reliability; Missing Data; Imputation Methods; Expectation Maximization Logarithm; Series Mean; Metacognitive Thinking.

تقدير الصدق والثبات لمقياس التفكير ما وراء المعرفي في ضوء نسب البيانات المفقودة وطرق تعويضها

باسل خميس سالم أبوفودة

تاريخ التسليم: (2024/2/26)، تاريخ القبول: (2025/1/7)، تاريخ النشر: ××××

الملخص: الهدف: تقدير الصدق والثبات لمقياس التفكير ما وراء المعرفي في ضوء نسب البيانات المفقودة وطرق تعويضها. ولتحقيق أهداف الدراسة جرى تطبيق مقياس للتفكير ما وراء المعرفي المكون من (42) فقرة، على عينة قوامها(382) طالباً جرى اختيارهم عشوائياً من طلبة الجامعة العربية المفتوحة في الأردن خلال العام الدراسي 2024/2023. **المنهج**: استخدمت الدراسة المنهج الوصفي التحليلي. **النتائج**: أشارت نتائج التحليل العاملي الاستكشافي أن قيم التباين المفسّر التراكمية بإستخدام طريقة لوغاريتم تعظيم التوقعات (EM) كانت أعلى مقارنة بالمجموعة المرجعية، بينما انخفض مقدار التباين المفسّر التراكمية بإستخدام أسلوب الوسط المتسلسل (SM). وأظهرت النتائج وجود فروق بين قيم معاملات ثبات كرونباخ ألفا وكذلك في قيم معاملات ثبات مكدونالد أوميغا لصالح طريقة لوغاريتم تعظيم التوقعات (EM) لجميع حالات نسب فقد البيانات مقارنة بالمجموعة المرجعية، بينما كانت الفروق لصالح المجموعة المرجعية مقارنة بأسلوب الوسط المتسلسل (SM). **الاستنتاجات**: أفضلية طريقة لوغاريتم تعظيم التوقعات (EM) لتعويض البيانات المفقودة مقارنة بالطرق الأخرى. **التوصيات**: استخدم طريقة لوغاريتم تعظيم التوقعات (EM) لتعويض البيانات المفقودة، وإجراء دراسة مقارنة في ضوء نسب فقد للبيانات وطرق تعويض مختلفة باستخدام مقاييس نفسية.

الكلمات المفتاحية: الصدق، الثبات، البيانات المفقودة، تعويض البيانات المفقودة، لوغاريتم تعظيم التوقعات، الوسط المتسلسل، التفكير ما وراء المعرفي..

1. Introduction:

Metacognitive thinking has received great interest among stakeholders and researchers in the field of education. Due to its importance in improving the way students think, it increases students' awareness of what they are studying. Metacognitive thinking enables students to assume multiple roles simultaneously when confronted with a problem in an educational setting. They can act as idea generators, planners, critics, creators of specific concepts, directors of particular approaches, and organizers of solution steps. Additionally, they present various options to their peers, evaluate each one, and select the most suitable. This process cultivates productive thinkers (Abu Al-Hajj, 2019).

1 Department Diploma in Education, College of Education, Arab Open University, Amman, Jordan.
* Corresponding author email: b_abufodeh@aou.edu.jo

1 قسم دبلوم التربية، كلية: التربية، الجامعة العربية المفتوحة، عمان، الأردن
* الباحث المراسل: b_abufodeh@aou.edu.jo

Due to the necessity of measuring metacognitive thinking, many studies have been conducted to construct metacognitive thinking scales and investigate their psychometric properties. However, there are several challenges that many researchers face when collecting and analyzing data, which in turn limit the quality of the results of statistical analysis as they affect their properties. Psychometrics is represented by validity and reliability, and one of these problems is related to missing data, which indicates that part of the data from the study sample is missing for some variables and items (Awad & Al-Momani, 2017).

The problem of missing individuals' responses to a number of scale items is one of the research issues that has received great attention from many researchers due to its expected impact on the psychometric properties of the scale. Handling the problem of missing data gains importance when it comes to the psychological or educational aspect, particularly when relying on these psychometric characteristics to make decisions related to selecting the items to be included in the scale (Al-Sarayrah, 2018).

The statistical methods used in data analysis always assume the presence of complete data on all variables used in the analysis. Therefore, missing data poses major challenges in the statistical analysis and interpretation of results. It leads to reducing the size of the analysis sample, reducing the power of the statistical test, reducing the accuracy of confidence intervals, and obtaining biased estimates that affect the psychometric properties of the scale, which, in turn, poses a threat. This clearly indicates the validity of the results and leads to inaccurate results (Carpita & Manisera, 2011; Kang, 2013). Bori (2013) emphasized that missing data presents a statistical problem. Statistical methods rely on having complete data for all relevant variables in the analysis. The presence of missing data reduces the sample size and raises concerns about the sample's representation of the population, thereby affecting the accuracy and introducing bias to the estimates of statistical parameters.

The literature identifies three types of missing data mechanisms: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). The following is a presentation of these types (Al-Banawi, 2021; Bhandari, 2022; Tamboli, 2021):

1. Missing Completely at Random (MCAR): is a situation where data is missing due to completely random reasons; there is no specific structure to describe this missingness.
2. Missing at Random (MAR): In this method the missing-ness is due to the underlying characteristics of the observation as a whole and can be predicted from other information (variables) of the observation.
3. Missing not at Random (MNAR): In this case, the probability of the data being missing is directly related to the value of the missing data itself. MNAR has a structure that is directly related to the missing observations themselves. Not properly recognizing MNAR would lead to a biased solution that is less effective in real-world applications.

Many researchers have focused on developing various methods to handle missing data. Methods for managing missing data can be categorized into two main groups, as follows:

First, the most widely used method for treating missing data is to delete the missing values. Due to its ease of application, this method involves excluding individuals with missing data from the analysis. This method assumes that the data was lost completely at random.

Second, Imputing Missing Values: In this approach, missing values are replaced with statistically derived values based on observed data, rather than removing individuals with missing data. This prevents the loss of valuable information. The current study utilizes two methods that are part of this approach (Little & Rubin, 2002).

1. The Expectation-Maximization Algorithm (EM) is a method used to estimate the compensatory value of missing data. It relies on successive approximation processes within an algorithm that comprises two steps: the expectation step and the maximization step. These steps are based on maximum likelihood estimation, aiming to obtain an estimate of the missing values.

2. Series Mean method (SM). In this method, missing values are estimated based on the arithmetic mean of the series within a single variable.

The literature indicates that there are other imputation methods such as (Little & Rubin, 2002; Schlomer et al., 2010; Witta, 2000; Zhou, 2001):

- Mean/Median/Mode Imputation: Replacing missing values with the mean, median, or mode of the column.

- Predictive Imputation: Using statistical models (like linear regression, k-nearest neighbors, etc.) to estimate the missing values based on other data.

− Interpolation and Extrapolation: For time series data, interpolate missing values based on surrounding data points.

− Using Algorithms Robust to Missing Data: Some algorithms can handle missing data internally. For instance, decision trees and random forests can manage missing values without imputation.

- Using Indicator Variables: Create a new binary variable that indicates whether data was missing for a particular observation and include it as a feature in your model.

− Multiple Imputation: Multiple imputation involves creating several different imputations (predictions) for each missing value and then averaging the results. It considers the uncertainty of the imputations and can provide more robust estimates.

− Last Observation Carried Forward (LOCF): In time series data, replacing the missing value with the last observed value. It's a straightforward approach but can introduce bias if the previous value is not representative.

- Machine Learning-Based Imputation: Advanced techniques like using deep learning models (e.g., autoencoders) can learn from the data's structure to impute missing values effectively.

Enders (2004) stated that it is rare to find a study without some degree of missing data. Finch (2008) emphasized that researchers who ignore how to handle missing data will have a negative impact on their results. Some researchers tend to overlook missing data because it is more convenient, they may not fully grasp the severity of the issue, or they lack awareness of the various methods available for addressing it.

Dealing with missing data requires expertise in statistical processes and experience with various analysis software that can handle missing data.

It is important to note that excluding individuals with missing data in this area can lead to biased results and weaken the statistical test's power (Rippe et al., 2013).

The literature indicates that there is no single optimal method for compensating for missing data (Dai, 2021). Many researchers have recommended using multiple methods to address missing data to compare results (Kwak & Kim, 2017).

Previous studies:

There have been numerous studies about missing values and the methods used to impute them. One study was conducted by Enders (2004) to investigate the impact of strategies for handling missing data on estimating the reliability of Likert scale data. Four methods were used to impute missing data. The results indicated that the Expectation Maximization algorithm (EM) yielded the least bias. The study suggests that researchers should consider the impact of missing data on reliability estimation and recommend using the Expectation Maximization algorithm (EM) for imputing missing values.

Cokluk and Kayri (2011) conducted a study to compare the construct validity of the predestination scale under conditions with no missing data and with missing data in various proportions, Using different imputation methods. The results indicated that the presence of missing data and using different imputation methods led to a decrease in the cumulative value of the explained variance, a decrease in the latent root values, and a decrease in the value of the Cronbach alpha reliability coefficient.

Hussein (2012) conducted a study on estimating missing values for the response variable in a multiple regression model. Two methods were used to estimate the missing value: the Expectation Maximization Algorithm and the Regression Imputation method. The results of the two methods were compared to those of the unconditional averaging method for handling missing data at different data loss ratios. The results showed that the Expectation Maximization Algorithm is superior to the Regression Compensation method when compared to the unconditional Average method.

Haiba (2013) conducted a study to investigate the impact of different methods for handling missing data (Multiple imputation, Regression analysis, and Maximum Likelihood Estimation) on the psychometric properties of a multiple-response scale. To achieve the study's objectives, data were generated using various sample sizes (50, 100, 200) and proportions of missing data (10%, 20%, 40%). The results indicated that the three methods did not have a significant effect on the values of the Cronbach alpha reliability coefficient. However, the Maximum Expectation Method had a slight advantage for loss ratios (40%).

The results indicated that there was no difference in the impact of the three methods on construct validity at a loss rate of 10% across all sample sizes. However, the results also showed that the regression analysis method had an advantage in maintaining construct validity even when loss rates were between 20% and 40%.

Zekeriya (2015) conducted a comparative study of five methods for imputing missing data: Complete Deletion, Regression Analysis, Multiple Imputation, Mean Substitution for all individuals who answered the scale item, and mean substitution using the individual's other responses. The study involved items with randomly Incomplete data, with varying levels of data loss (5%, 10%, 20%) and sample sizes (150, 650). The study investigated the impact of various research positions on the latent root values, Cumulative Explained Variance values, and Cronbach Alpha reliability coefficient values. The results indicated that the Multiple Imputation Method and the Regression Method produced similar values, or values as close as possible to those obtained in the case of complete data. The results indicated that there were no statistically significant differences ($\alpha = 0.05$) between the values estimated by imputation methods and the completed data sets.

Akbas and Tavsancil (2015) conducted a study to estimate the values of the Cronbach's reliability coefficient alpha, the values of the McDonald's reliability coefficient omega, and the Omega reliability coefficient w while imputing for missing data. (100) sets of data were generated with varying sample sizes (250, 500, 1000) and numbers of items (10, 15). Data missing occurred at a proportion of (5%, 10%) using the Completely Random Loss method, the Random Loss Method, and the Non-random Loss Method. Missing data were replaced using various methods, including the Expectation Maximization Method, Multiple imputation Method, Regression Analysis Method, Donor Imputation Method, and Complete Case Analysis Method. The results indicated that the Complete Deletion Method may lead to significant issues, while the Expectation Maximization and Multiple Imputation Methods outperformed the others. The analysis results did not indicate a Superior Compensation Method in every situation.

Béland and his colleagues (2016) conducted a study to investigate the impact of ten methods for compensating for missing data on the values of the Cronbach Alpha reliability coefficient. To achieve the study's objectives, data were generated for research situations (50, 250, 500) with 20 and 60 items and with percentages of missing data (20%, 50%) using both the Random Missing Method and the Completely Random Missing Method. The results indicated that the Multiple Compensation Method consistently yielded the highest Cronbach Alpha reliability coefficient and the lowest standard error across all research situations.

Matysova (2019) conducted a study to investigate the impact of various factors (reliability values, sample size, percentage of missing data, and method of compensating for missing data) on the values of Cronbach's Alpha reliability coefficient. To achieve the objectives of the study, data were generated with different sample sizes (50, 100), and data loss was performed using Completely Random Missing, Random Missing Method and Non-random Missing Method, with missing data proportions (5%, 15%). The results indicated that when the percentage of missing data is low, the missing data method is Completely Random, and the sample size is large, both the Multiple Imputation and Deletion Methods yield similar results. However, the Multiple Imputation Method outperforms the Deletion Method by showing less bias, a wider confidence interval, and a lower mean. For error boxes, this occurs when the loss is either random or non-random.

The results indicate that using the Listwise Deletion Method decreases the value of the Cronbach Alpha reliability coefficient. On the other hand, the Multiple Imputation Method shows an increase in the value of the Cronbach Alpha reliability coefficient when the missing is Completely Random or Random, but a decrease when the missing is not random.

Xueying and his colleagues (2020) conducted a study to compare the accuracy of four methods for handling missing data: The Direct Deletion method, the Arithmetic Mean Imputation Method, the Donor Imputation Method, and the Multiple Imputation Method. The study used missing data rates (5%, 10%, 15%, 20%). The comparison was based on the absolute deviation, the square root of the average squared errors, and the relative error rate values. The results indicate that both the Multiple Compensation Method and the Donor Compensation Method showed the least bias and the lowest standard deviation for various percentages of missing data. Furthermore, the performance of both methods was superior to that of the direct deletion method and the Arithmetic Mean Compensation Method.

Al-Banawi (2021) conducted a study to investigate the impact of various methods for replacing missing values (Arithmetic Mean, Linear Trend Point, and Approximate Value) on the development of a quality-of-life measure for Jordanian university students. To achieve the objectives of the study, a random data loss of 10% was implemented. Missing values were replaced using three different methods. The results indicated that all three methods effectively replaced missing values, preserved the factorial structure of the scale, and produced data that achieved all forms of equivalence with the original scale data.

Most studies have focused on explaining the optimal methods for imputing missing data or comparing these methods without paying attention to the scale itself or its psychometric properties. Additionally, most studies rely on simulated data.

Therefore, there are still other aspects in this field that require further research and in-depth study, especially when considering actual data. The present study aimed to address the gap by creating a scale tool with robust psychometric properties, which is a unique aspect of the study. This was achieved by analyzing the coefficients of Cronbach's Alpha reliability, McDonald's Omega reliability coefficient, and Cumulative Explained Variance for the Metacognitive Thinking Scale in relation to the proportion of missing data and potential methods for imputation.

Study Problems:

Previous research has focused on various methods for imputing missing data to assess their impact on the psychometric properties of different scales. Most studies have focused on explaining the optimal methods for imputing missing data or comparing these methods without paying attention to the scale itself or its psychometric properties. Additionally, most studies rely on simulated data.

Therefore, there are still other aspects in this field that require further research and in-depth study, especially when considering actual data. The present study aimed to address the gap by creating a measurement tool with robust psychometric properties, which was a unique aspect of the study. This was achieved by analyzing the coefficients of Cronbach's alpha reliability, McDonald's omega reliability coefficient, and cumulative explained variance for the metacognitive thinking scale in relation to the proportion of missing data and potential methods for imputation.

Research questions:

Based on the importance of addressing missing values in statistical analysis and the potential impact of using inappropriate methods for handling missing data, this study aimed to investigate the following research questions:

1. Is there a statistically significant difference ($\alpha = 0.05$) in the values of the Cronbach Alpha reliability coefficients for the Metacognitive Thinking Scale based on the researchers' positions regarding the proportions of missing data (5%, 10%, 30%) and the use of the imputation methods (EM, SM)?
2. Is there a statistically significant difference ($\alpha = 0.05$) in the values of the McDonald Omega reliability coefficients for the Metacognitive Thinking Scale based on the researchers' positions regarding the proportions of missing data (5%, 10%, 30%) and the use of the imputation methods (EM, SM)?
3. Is there a statistically significant difference ($\alpha = 0.05$) in the Cumulative Explained Variance values for the Metacognitive Thinking Scale based on the researchers' positions regarding the proportions of missing data (5%, 10%, 30%) and the use of the imputation methods (EM, SM)?

Objectives of the study:

This study aimed to estimate the validity by calculating the cumulative percentage of explained variance and reliability coefficients of Cronbach's Alpha and McDonald's Omega for the Metacognitive Thinking Scale while considering the proportions of missing data and the method of imputation used.

The importance of study:

The theoretical importance of the current study lies in identifying the most effective imputation method for addressing missing data. To obtain reliable psychometric properties for the scale.

From a practical standpoint, the importance of the study lies in its introduction to a topic that is of interest to many researchers and individuals in the field of statistical analysis: how to manage missing data. To improve confidence in research findings. The current study provides a measurement tool with robust psychometric properties for assessing metacognitive thinking among university students and used two imputation methods for missing data: The Expectation-Maximization Algorithm (EM) and The Series Mean (SM).

Terminology of the study:

− Missing Data: is represented by the individual not responding to some items of the Metacognitive Thinking Scale regardless of the reason for that.

− Imputation Methods refer to techniques used to handle missing data: It is the value that is placed in place of the missing value after processing it using one of the methods of dealing with missing data (Expectation-Maximization Algorithm (EM) and the Series Mean (SM)) through the available data.

2. Methods and Procedures:

Study Methodology: Utilizing the Descriptive Approach.

Study Population and Sample:

The study population consists of (2200) students registered at the Arab Open University in Jordan during the academic year 2023/2024. A simple random sample using tables of random numbers consisted of (382) students from various academic programs was selected from the university.

Study tool:

To achieve the study's objectives, a Scale of Metacognitive Thinking was developed by referring to theoretical literature and previous studies such as (Schraw & Dennison, 1994; Kumar, 1998; Abdalqader, 2012; Al-Hamouri & Abu Mokh, 2011). The scale consists of (52) items. The scale was initially presented of (10) arbitrators who are specialists from universities.

After collecting the arbitrators' suggestions and opinions on the items of the scale, some of the items were rephrased linguistically, some were adjusted, others were combined, and some irrelevant items were removed.

The number of items that the researcher modified linguistically was (7 items), and (4 items) were merged; due to their inclusion in other items, and not their repetition, and the items that obtained an agreement rate of (90%) or more among the arbitrators were kept. The scale in its final form consisted of (42) items.

Responses were assigned to the scale items using a five-point Likert scale, with the following levels defined: always (5), often (4), sometimes (3), rarely (2), never (1).

The scale was utilized in a survey of 150 students to confirm its validity and reliability. The validity of the scale was confirmed through an Exploratory Factor Analysis (EFA) using the Principal Components Analysis Method with Varimax Rotation and a predetermined number of extracted factors.

The results revealed the presence of three factors that influence Metacognitive Thinking with eigenvalues greater than one. The first factor explained (17.983%) of the total variances, and all factors explained (53.10%) of the total variance. The eigenvalue of the first factor was (15.720), the second factor was (7.553), and the third factor was (6.695).

The results showed 18 items with a loadings factor of 0.40 and above for the Regulating Cognition dimension (RC), 13 items for the Knowledge of Cognition dimension (KC), and 11 items for the Cognitive Processing dimension (CP).

The scale was applied to a sample of 382 students to verify the scale's theoretical structure. AMOS V.23 program was used to analyze the results. Table (1) shows the results of the fit indicators:

Table (1)

The Results of fit indicators.

The indicator value	Indicator
1.301	χ^2
0.881	GFI
0.894	AGFI
0.909	NFI
0.911	CFI
0.924	TLI
0.902	IFI
0.067	RMR
0.077	RMSEA

Table (1) shows that all fit indicators are within the accepted standard. All standard weights of the items, which represent the loadings of the factors, have exceeded (50%).

Figure 1 shows the correlation coefficients between the items and dimensions of the scale were assumed in the theoretical construction of the scale:

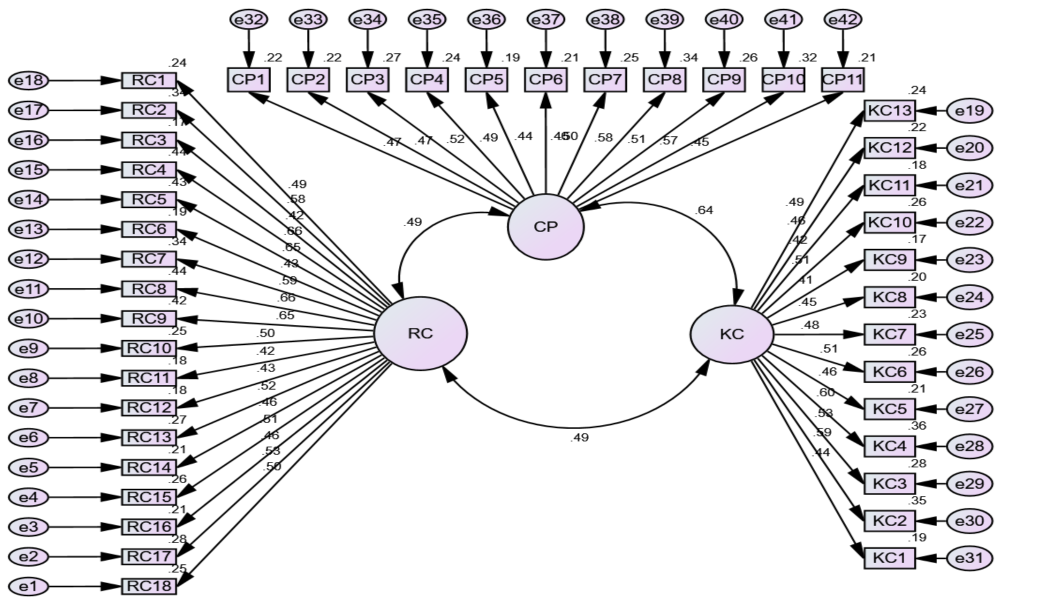

Figure 1. The measurement model of the scale.

The Cronbach's Alpha reliability coefficient for the study tool was (0.89), the value of the split-half reliability coefficient corrected with the Spearman-Brown equation was (0.86), the value of the McDonald's Omega reliability coefficient was (0.91), and the Cronbach Alpha reliability coefficients for the dimensions ranged between (0.84 - 0.88). The values are high, exceeding the limit (0.70) (Pallant, 2005). Based on the previous indicators, it is evident that the scale used demonstrates a high level of validity and reliability.

Data collection:

The Metacognitive Thinking Scale was administered to the study sample. The statistical software (SPSS V.27) and (AMOS V.23) were used to conduct the required statistical analyses to answer the study questions.

The analysis data was reviewed, and it was found that all respondents had complete data on the scale, thus forming the reference group data.

Data missing in the reference group was simulated using a Completely Random Method, with the following missing ratios: (5%, 10%, 30%). Two methods were used to impute the data: the Expectation-Maximization Algorithm (EM) method and the Series Mean (SM) method. Both methods assume that data missing is Completely Random.

The assumptions of the Expectation-Maximization Algorithm (EM) method were verified is an iterative method for estimating parameters in statistical models. The goal is to maximize the likelihood function given the latent variables. It starts with an initial estimation of the parameters, then alternates between two steps: an expectation step (E) to estimate the latent variables and a maximization step (M) to update the parameters

Table No. (2) shows the results of Little's test to examine complete randomness for missing data:

Table No. (2)

The results of Little's test for assessing the Completeness of Randomness in missing data.

Research Situations (Proportion of Missing Data)	Chi-Square χ2	DF	Sig.
5%	37845.354	38645	0.401
10%	38687.645	36112	0.498
30%	65217.745	29783	0.512

It is noted from Table No. (2) that the values of Chi-square are not statistically significant ($\alpha = 0.05$), and this indicates that data missing in all research situations was Completely Random.

Data Analysis:

- Estimating reliability using the Cronbach Alpha method and the McDonald Omega reliability coefficient.
- Exploratory factor analysis to calculate the Cumulative Percentage of Explained Variance.
- Little's test to estimate the complete randomness of missing data.
- Use two methods to imputation data: the Expectation-Maximization Algorithm (EM) method and the Series Mean (SM) method.

To detect the function of the binary differences between two reliability coefficients for a paired sample, as well as the binary differences between the correlation coefficients, the AlSawalmeh and Feldt equation (Alsawalmeh & Feldt, 1994) was used, as follows:

$$W = \frac{1-\alpha_2}{1-\alpha_1} * (F_{v,v})$$

$$v = \frac{N-1-7r_{12}^2}{1-r_{12}^2}$$

where:

N: The total number of individuals.

$\propto_1$: The largest value of the reliability coefficient.

$\propto_2$: The minimum value of the reliability coefficient.

r^2_{12}: the square of the correlation coefficient between the raw scores in the first and second methods.

The (F (v1, v2)) is calculated through the following equation:

$$v_1 = \frac{2M}{M-1}$$

$$v_2 = \frac{2M^2}{V*(2-M)-M^2(M-1)}$$

$$M = \frac{(N-1)c_1}{(N-3)(c_1-2)} - \frac{2}{N-1}(r_{12}^2)$$

$$V=\frac{(N+1)(N-1)(c_2+2)c_1^2}{(N-3)(N-5)(c_1-2)(c_1-4)c_2}-\frac{(N-1)^2c_1^2}{(N-3)^2(c_1-2)^2}-\frac{4r_{12}^2}{N-1}$$

(C1, C2) are calculated as follows:

$$c_1=(N-1)*(k_1-1)$$

$$c_2=(N-1)*(k_2-1)$$

where:

N: Sample Size.
K_1: The number of scale items in the first form.
K_2: The number of scale items in the second form

3. Results:

The results related to the first study question and their discussion: Is there a statistically significant difference (α = 0.05) in the values of the Cronbach Alpha reliability coefficients for the Metacognitive Thinking Scale based on the researchers' positions regarding the proportions of missing data (5%, 10%, 30%) and the use of the imputation methods (EM, SM)?

To answer the study question, the values of the Cronbach Alpha reliability coefficients for the Metacognitive Thinking Scale for research positions were calculated according to the proportions of missing data and the method of imputation. To reveal the significance of the difference between the two reliability coefficients for a paired sample, the researcher used the Al-Sawalmeh and Feldt equation (Alsawalmeh & Feldt, 1994). Table No. (3) shows the results of the analysis:

Table No. (3)

The results of the (W) test to detect the differences between Cronbach's Alpha reliability coefficients.

Group/data Imputation Method	Proportions of Missing Data	The Square of the Correlation Coefficient r^2_{12}	Cronbach's Alpha	The value of (W) test.	Critical value (F)	Standard Error of Measurement
Reference group	%0	0.9025	0.9411	1.310	1.11	6.8897
Expectation Maximization (EM)	%5		0.9501			5.9901
Reference group	%0	0.9801	0.9411	1.400	1.11	6.8897
Expectation Maximization (EM)	10%		0.9532			6.0035
Reference group	%0	0.9216	0.9411	1.640	1.11	6.8897
Expectation Maximization (EM)	%30		0.9601			6.1013
Reference group	%0	0.8836	0.9411	1.320	1.11	6.6458
Series Mean (SM)	%5		0.9301			7.0112
Reference group	%0	0.8930	0.9411	1.340	1.11	6.4956
Series Mean (SM)	10%		0.9288			7.4578
Reference group	%0	0.9235	0.9411	1.930	1.11	6.6780
Series Mean (SM)	%30		0.8978			8.1145

It is noted from Table No. (3) that all values of Cronbach's Alpha reliability coefficients when using the Expectation Maximization (EM) logarithm method for imputation of missing proportions of data were higher compared with using the Series Mean (SM) method. This result differed from the results of a study (Akbas & Tavsancil, 2015; Zekeriya, 2015), and this difference may be due to different research positions.

It was noted that the values of Cronbach's Alpha reliability coefficients when using the Expectation-Maximization (EM) Logarithm Method did not differ relatively with an increasing proportion of missing data, while the values of Cronbach's Alpha reliability coefficients decreased with an increasing proportion of missing data when using the Series Mean (SM) imputation method.

The values of the Squared Correlation Coefficients (R^2) ranged between (0.8836 - 0.9801). The highest value of the Squared Correlation Coefficient - the explained variance - was between (Reference group) and (Expectation Maximization (EM) when the proportions of missing data (10) %) where the value (0.9801); this value indicates the highest proportion of explained variance by the two research positions.

Therefore, (98.01%) of the value variation (the scale used) can be explained using the linear relationship between the two methods of imputation for missing data, and that the remaining percentage (1.99%) is due to other factors.

The results related to the second study question and their discussion: Is there a statistically significant difference (α = 0.05) in the values of the McDonald Omega reliability coefficients for the Metacognitive Thinking Scale based on the researchers' positions regarding the proportions of missing data (5%, 10%, 30%) and the use of the imputation methods (EM, SM)?

To answer the study question, the values of the McDonald Omega reliability coefficients for the Metacognitive Thinking Scale for research positions were calculated according to the proportions of missing data and the method of imputation. To reveal the significance of the difference between the two reliability coefficients for a paired sample, the researcher used the Al-Sawalmeh and Feldt equation (Alsawalmeh & Feldt, 1994). Table No. (4) shows the results of the analysis:

Table No. (4)

The results of the (W) test to detect the differences between McDonald Omega reliability coefficients.

Group/data Imputation Method	Proportions of Missing Data	The Square of the Correlation Coefficient r^2_{12}	McDonald Omega	The value of (W) test.	Critical value (F)	Standard Error of Measurement
Reference group	%0	0.9901	0.9411	1.250	1.11	6.7891
Expectation Maximization (EM)	%5		0.9477			6.3564
Reference group	%0	0.9899	0.9411	1.310	1.11	6.7891
Expectation Maximization (EM)	10%		0.9501			6.1346
Reference group	%0	0.9854	0.9411	1.590	1.11	6.7891
Expectation Maximization (EM)	%30		0.9588			6.0110
Reference group	%0	0.9891	0.9411	1.480	1.11	6.7891
Series Mean (SM)	%5		0.9214			7.1625
Reference group	%0	0.9786	0.9411	1.610	1.11	6.7891
Series Mean (SM)	10%		0.9147			7.5481
Reference group	%0	0.9584	0.9411	2.530	1.11	6.7891
Series Mean (SM)	%30		0.8655			7.9987

It is noted from Table No. (4) that all values of the McDonald Omega reliability coefficients when using the Expectation Maximization Logarithm Method (EM) to impute missing proportions of data were higher compared to the Series Mean Method (SM).

It is noted that the values of the McDonald-Omega reliability coefficients when using the Expectation Maximization Method (EM) did not differ significantly with the increasing proportion of missing data. The results showed that all values of the McDonald-Omega reliability coefficients decrease with increasing proportions of missing data when using the Series Mean method (SM).

The values of the Squared Correlation Coefficients (R^2) ranged between (0.9584 - 0.9901). The highest value of the Squared Correlation Coefficient - the explained variance - was between (Reference group) and (Expectation Maximization (EM) when the proportions of missing data (5) %) where the value (0.9901); this value indicates the highest proportion of explained variance by the two research positions.

Therefore, (99.01%) of the value variation (the scale used) can be explained using the linear relationship between the two methods of imputation for missing data, and that the remaining percentage (0.99%) is due to other factors.

The results related to the third study question and their discussion: Is there a statistically significant difference ($\alpha = 0.05$) in the Cumulative Explained Variance values for the Metacognitive Thinking Scale based on the researchers' positions regarding the proportions of missing data (5%, 10%, 30%) and the use of the imputation methods (EM, SM)?

An Exploratory Factor Analysis (EFA) was conducted using the Principal Components Analysis method with Varimax Rotation and extracting the cumulative percentage of explained variance. To detect the significance of the difference between two correlation coefficients for a paired sample, the researcher used the Al-Sawalmeh and Feldt equation (Alsawalmeh & Feldt, 1994). Table No. (5) shows the results of the analysis:

Table No. (5)

The explained variance and the results of the (W) test to detect differences between two correlation coefficients.

Group/data Imputation Method	Proportions of Missing Data	EFA		The Square of the Correlation Coefficient r^2_{12}	The Average of the r_{12}	The value of (W) test.	Critical value (F)
		Cumulative Explained Variance	Correlation Coefficient r_{12}				
Reference group	%0	0.5312	0.6266	0.9956	0.6371	1.180	1.11
Expectation Maximization (EM)	%5	0.5469	0.6475				
Reference group	%0	0.5312	0.6266	0.9912	0.6482	1.250	1.11
Expectation Maximization (EM)	10%	0.5678	0.6698				
Reference group	%0	0.5312	0.6266	0.9798	0.7056	1.920	1.11
Expectation Maximization (EM)	%30	0.5997	0.7846				

Reference group	%0	0.5312	0.6266	0.9998	0.6195	1.160	1.11
Series Mean (SM)	%5	0.5103	0.6124				
Reference group	%0	0.5312	0.6266	0.9874	0.6140	1.134	1.11
Series Mean (SM)	10%	0.5211	0.6014				
Reference group	%0	0.5312	0.6266	0.9781	0.6359	1.113	1.11
Series Mean (SM)	%30	0.5300	0.6451				

It is noted from Table No. (5) that the Cumulative Explained Variance values using the Expectation Maximization Logarithm Method (EM) to impute missing data in all cases of missing data were higher compared to the cumulative explained variance values in the reference group. It is also noted that the Cumulative Explained Variance values increase with the increasing proportion of missing data that has been imputed.

The results showed that the Cumulative Explained Variance values decreased using the Series Mean Method (SM) in cases of missing data proportions (5% and 10%), then increased using the Series Mean Method (SM) in the case of missing data proportion (30%), but to a smaller extent compared to using the Expectation Maximization Logarithm Method (EM) in the case of missing data proportion (30%).

The values of Squared Correlation Coefficients (R^2) ranged from 0.9781 to 0.9998. The highest value of the Squared Correlation Coefficient - the explained variance - was between (Reference group) and (Series Mean (SM) when the proportions of missing data (5) %) with the value of (0.9998). This indicates that the explained variance was at its highest between these two research approaches.

Therefore, (99.98%) of the value variation (the scale used) can be explained using the linear relationship between the two methods of imputation for missing data, and that the remaining percentage (0.02%) is due to other factors.

4. Discussions:

The results (Table No. (3)) showed that the values of the Cronbach Alpha reliability coefficients in the reference group with the research situations using the Expectation-Maximization Logarithm Method, the results showed that all values were statistically significant (α = 0.05) in favor of the Expectation-Maximization Logarithm Method (EM). While the results of the comparison between the values of Cronbach's Alpha reliability coefficients for the research positions using the Series Mean method and the reference group showed that all values are statistically significant (α = 0.05) in favor of the reference group.

The results of the study are consistent with the results of the study (Enders, 2004), which showed the superiority of the Expectation-Maximization Logarithm Method (EM) in estimating the Cronbach Alpha reliability coefficient.

The results differ from the study Cokluk and Kayri (2011) in the results related to the (EM) method.

The reason may be attributed to the small size of the study sample and the target group, as well as the type of information required to be answered, and the difference in the reason for missing data, in addition to the difference in research positions, as Dai (2021) indicated that the different methods of compensating for missing data embody different assumptions related to mechanisms for dealing with data. Missing data, how the missing data is distributed, and the reasons for missing data.

It is noted from the results of the analysis that the values of the Standard Errors of Measurement using the Expectation Maximization Logarithm Method (EM) were lower compared to the values of the Standard Errors of Measurement using the Series Mean Method (SM).

All values of the Standard Errors of Measurement using the Expectation Maximization Logarithm Method (EM) were lower than compared to the values of the Standard Errors of Measurement in the reference group, and the values of the Standard Errors of Measurement decreased with an increasing proportion of missing data using the Expectation Maximization Logarithm Method (EM).

Regarding the values of the Standard Errors of Measurement using the Series Mean Method (SM), they were higher in all cases of missing data compared to the values of the Standard Errors of Measurement in the case of the reference group. The values of Standard Errors of Measurement increased with an increasing proportion of missing data using the Series Mean method (SM). The results of the current study differ from the results of the studies of (Matysova, 2019; Béland et al., 2016), and the reason may be attributed to the difference in the reason for missing data, and the difference in research positions.

The results (Table No. (4)) showed that the values of the McDonald Omega reliability coefficients in the reference group with the research situations using the Expectation Maximization Logarithm method (EM) with different proportions of missing data, the results showed that all values are statistically significant (α = 0.05) in favor of the (EM) with different proportions of missing data. The results of the comparison between the values of the McDonald Omega reliability coefficients in the reference group and the research situations using the Series Mean method (SM) showed that all values are statistically significant (α = 0.05) in favor of the reference group.

The previous results are consistent with the results of comparing the values of the Cronbach Alpha reliability coefficients, this indicates the possibility of using the McDonald Omega reliability coefficient instead of the Cronbach Alpha reliability coefficient. It gives close results for the Cronbach Alpha reliability coefficient without being subject to the assumptions required by calculating the Cronbach Alpha reliability coefficient, which are difficult to achieve in many studies.

It is noted from the results of the analysis that the values of the standard errors in the measurement using the Expectation Maximization Logarithm Method (EM) were lower compared to the values of the standard errors in the measurement using the Series Mean method (SM).

All values of the standard errors in the measurement using the Expectation Maximization Logarithm Method (EM) were lower than compared to the values of the Standard Errors of Measurement in the reference group, and the values of the Standard Errors of Measurement decreased with an increasing proportion of missing data using the Expectation Maximization Logarithm Method (EM).

Regarding the values of Standard Errors of Measurement using the Serial Mean method (SM), all cases of missing data were higher compared to the values of Standard Errors of Measurement in the case of the reference group, and the values of Standard Errors of Measurement increased with an increasing proportion of missing data using the Series Mean method (SM). The previous result differs from the results of the study (Xueying et al., 2020), and this difference may be attributed to the difference in sample size, target group, and data collection tool.

The results (Table No. (5)) showed that the values of the correlation coefficients for the reference group with the research positions for the proportions of missing data and the method of imputation of them using the Expectation Maximization Logarithm Method (EM), the results showed that all values are statistically significant ($\alpha = 0.05$) in favor of the research positions using the (EM). The results of comparing the values of the correlation coefficients of the reference group with the research positions for proportions of missing data using the Series Mean Method (SM) showed that all values are statistically significant ($\alpha = 0.05$) in favor of the reference group.

The results of the current study are consistent with the results of the study (Akbas & Tavsancil, 2015), while the current results differ with the results of the study (Cokluk & Kayri, 2011; Zekeriya, 2015). This difference may be attributed to the difference in research positions as well as the type of information required, in addition to the different categories of respondents.

The results related to the Series Mean Method (SM) showed that the amount of Cumulative Explained Variance to imputation for missing proportions is less than in the case of non-missing, and this result is partially consistent with the results of a study (Cokluk & Kayri, 2011; Akbas & Tavsancil, 2015).

Limitations of the study

This study focused on two methods for imputing missing data: the Expectation-Maximization algorithm and the Series Mean Method.

Recommendations:

In light of the results of the study, the following recommendations were made:

- The possibility of using the Expectation Maximization Logarithm Method (EM) for imputation of missing data with different data loss proportions is because the estimates of reliability values were higher compared to the Serial Mean Method (SM), and the values of Standard Errors of Measurement with different loss proportions were lower when using the Expectation Maximization Logarithm Method (EM).
- Avoid arbitrary selection when using different methods of imputation for missing data, and do not be satisfied with one imputation method.
- Conducting studies using imputation methods for missing data in new research situations and using different scales.

Disclosure Statement:

- **Ethical approval and consent to participate**: This study was approved by the Ethical Review Board of [Arab Open University]. All participants provided written informed consent before their inclusion in the study.
- **Availability of data and materials**: All data generated or analyzed during this study are included in this published article and its supplementary information files
- **Author contribution**: The Author designed the study, collected the data, analyzed the data, and wrote the manuscript.
- **Conflict of interest**: The author declares no conflict of interest.
- **Funding:** No funding was received for this study.
- **Acknowledgments:** The author would like to thank [Arab Open University, Jordan] for their valuable support and assistance during the study.

Open Access

References

- Abu Al-Hajj, M. (2019). The degree of teachers' use of metacognitive thinking skills in the Directorate of Education in the University District and its relationship to students' academic excellence and creativity. *Journal of Educational Sciences Studies, 46*(2), 375-403.
- Abdalqader, K. (2012). The Impact of Guided Discovery Approach in Developing Meta Cognitive Thinking and Achievement in Math among 9th Grade Students in Gaza Governorates. *An-Najah University Journal for Research - B (Humanities), 26*(9), 2131–2160. https://doi.org/10.35552/0247-026-009-006
- Akbas, U., & Tavsancil, E. (2015). Investigation of psychometric properties of scales with missing data techniques for different sample sizes and missing data patterns. *Journal of Measurement and Evaluation in Education and Psychology-EPOD, 6*(1), 38-57.
- Al-Banawi, A. (2021). Invariance of the quality-of-life scale according to missing values handling methods. *Humanitarian and Natural Sciences Journal, 2*(10), 42-49.
- Al-Hamouri, F., & Abu Mokh, A. (2011). Level of the Need for Cognition and Metacognitive Thinking among Yarmouk University Undergraduate Students. *An-Najah University Journal for Research - B (Humanities), 25*(6), 1463–1488. https://doi.org/10.35552/0247-025-006-001
- Al-Sarayrah, R. (2018). The effect of the percentage of missing values and the method of processing them on the accuracy of estimating the maximum value of the item information function and the value of the item reliability index. *Journal of Educational Science Studies, 45*(4), 485-501.
- Al-Sawalmeh, Y., & Feldt, L. S. (1994). A modification of Feldt's test of the equality of two dependent alpha coefficients. *Psychometrika, 59*(1), 49-57.

- Awad, A. B., & Momani, K. (2018). Recognizing the Importance of Dealing with Missing Data in Research Questionnaires and Test Students of the Faculty Members at King Faisal University. *An-Najah University Journal for Research - B (Humanities), 32*(6), 1033–1062. https://doi.org/10.35552/0247-032-006-002
- Béland, S., Pichette, F., & Jolani, S. (2016). Impact on Cronbach's α of simple treatment methods for missing data. *The Quantitative Methods for Psychology, 12*(1), 57-73.
- Bhandari, P. (2022). Missing data | Types, explanation, & imputation. *Scribbr.* https://www.scribbr.com/statistics/missing-data/
- Bori, M. S. (2013). *Dealing with missing data: Key assumptions and methods for applied analysis*. Paper published in fulfillment of the requirements for PM931 Directed Study in Health Policy and Management under Professor Cindy Christiansen.
- Carpita, M., & Manisera, M. (2011). On the imputation of missing data in surveys with Likert-type scales. *Journal of Classification, 28*(1), 93-112. https://doi.org/10.1007/s00357-011-9074-z
- Cokluk, O., & Kayri, M. (2011). The effects of methods of imputation for missing values on the validity and reliability of scales. *Educational Sciences: Theory & Practice, 11*(1), 303-309.
- Dai, S. (2021). Handling missing responses in psychometrics: Methods and software. *Educational Psychology, 3*(4), 673-693. https://doi.org/10.3390/psych3040043
- Enders, C. K. (2004). The impact of missing data on sample reliability estimates: Implications for reliability reporting practices. *Educational and Psychological Measurement, 64*(3), 419–436. https://doi.org/10.1177/0013164403261050
- Finch, H. (2008). Estimation of item response theory parameters in the presence of missing data. *Journal of Educational Measurement, 45*(3), 225-245.
- Haiba, M. (2013). Effects of missing data imputation on the psychometric properties of the multiple response scales: Empirical and simulation study. *Ain Shams University Journal of Measurement and Evaluation, 3*(5), 1-57.
- Hussein, A. N. (2012). Estimating the lost value of responding variable in the multi regression model. *Journal of Economic Sciences, 30*(8), 231-246.
- Kang, H. (2013). The prevention and handling of missing data. *Korean Journal of Anesthesiology, 64*(5), 402-406.
- Kumar, A. (1998). *The influence of metacognition on managerial hiring decision making: Implications for management development*. (Unpublished doctoral dissertation). Virginia Polytechnic Institute and State University.
- Kwak, S. K., & Kim, J. H. (2017). Statistical data preparation: Management of missing values and outliers. *Korean Journal of Anesthesiology, 70*(4), 407-411. https://doi.org/10.4097/kjae.2017.70.4.407
- Little, R., & Rubin, D. (2002). *Statistical analysis with missing data*. Wiley.
- Matysova, K. (2019). Evaluation of modern missing data handling methods for coefficient alpha. *Public Access Theses and Dissertations from the College of Education and Human Sciences, 347*. https://digitalcommons.unl.edu/cehsdiss/347
- Pallant, J. (2005). *SPSS survival manual: A step-by-step guide to data analysis using SPSS for Windows (Version 12)* (2nd ed.). Open University Press.
- Rippe, R., Den Heijer, M., & Le Cessie, S. (2013). Imputation of missing data. *Nederlands Tijdschrift Voor Geneeskunde, 157*(18), 39-55.
- Schlomer, G. L., Bauman, S., & Card, N. A. (2010). Best practices for missing data management in counseling psychology. *Journal of Counseling Psychology, 57*, 1-10.
- Schraw, G., & Dennison, R. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology, 19*, 460–475.
- Tamboli, N. (2021). Effective strategies for handling missing values in data analysis. *Analytics Vidhya*. https://www.analyticsvidhya.com/blog/2021/10/handling-missing-value/
- Witta, E. L. (2000). *Effectiveness of four methods of handling missing data using samples from a national database*. Paper presented at the Annual Meeting of the American Educational Research Association, New Orleans, LA.
- Xueying, X., Leizhen, X., Qimeng, Z., Shaoning, W., Mingcheng, W., & Hongbo, L. (2020). The ability of different imputation methods for missing values in mental measurement questionnaires. *BMC Medical Research Methodology, 20*(1), 1-9. https://doi.org/10.1186/s12874-020-00932-0
- Zekeriya, N. (2015). Comparison of various methods used in solving missing data problems in terms of psychometric features of scales and measurement results under different missing data conditions. *International Online Journal of Educational Sciences, 7*(4), 252–265.
- Zhou, Q. (2001). *Missing value imputation methods for parameter estimates and psychometric properties of Likert measures*. (Unpublished doctoral dissertation). University of Maryland.