User friendly science Package of R Programming Language: A Veritable Tool for Reliability Estimate of Non-cognitive Scale

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Abstract

Having quality instruments is essential in ensuring data integrity. Indiscriminately application and over-dependency on Cronbach alpha index for multiple measured items (ordinal scale) and usage of SPSS software, which produce spurious estimation, have been a subject of technical debates in the literature. This debate toes the path of fulfilling stringent underlying assumptions of Cronbach alpha, such as uni-dimensionality, tau-equivalent, etc. However, modern approaches like ordinal alpha, Omega coefficient, GLB, Guttman Lambda, and Revelle Beta have been suggested with precise estimates and confidence intervals via R programming language. Thus, this paper examined the performance of alternative approaches to Cronbach alpha and documented practical step by step of establishing it. Non-experimental design of scale development research was adopted, and a multi-stage sampling procedure was used to sample N = 883 subjects that participated in the study. Findings showed that the instrument is multidimensional, in which Cronbach alpha is not apt for its estimation. Also, other forms of reliability methods produced better and more precise estimates, though their performance differs among themselves. The authors concluded that estimation of Cronbach Alpha using SPSS when the instrument is ordinal is absolutely not sufficient. Therefore, it is recommended that researchers explore and shift their paradigm from traditional reliability estimates through SPSS to modern approaches using an R programming language.

***Keywords:** Ordinal Alpha, Cronbach Alpha, MacDonald Omega, Guttman Lambda, Revelle Beta, GLB, Userfriendlyscience Package, R programming Language*

Introduction

A human learning domain measurement is categorised into three: cognitive, affective, and psycho-productive [1]. The cognitive is used to measure the mental operations of individuals, which is measured with various cognitive instruments depending on the area of concern. At the same time, affective relates to attitude, interest, and perception of individuals, and psycho-productive behaviour relates to skills of an individual measured with various non-cognitive instruments. These instruments must meet the required benchmark of psychometric properties, including validity and reliability, before they can be used to gather acceptable data for decision-making. Reliability estimate is an integral part of every research as instruments to be used are expected to possess a level of consistency over time when reused, after ensuring those instruments are measuring what they are expected to measure (validity). However, [2]. [3] remarked that in determining an estimate of reliability, there had been various concerns about the use and misuse of some reliability estimates for what it was not meant for, which has provoked advocating for the use of appropriate and modern estimates based on what it was designed for.

There are numerous methods advanced by researchers used to estimate the reliability of non-cognitive instruments. These include Cronbach Alpha [4], Ordinal Alpha [5], Omega coefficient [6], Revelle Beta coefficient [7], [8], Greatest Lower Bound (GLB) [9] and many more. More importantly, the most pronounced reliability estimate used repeatedly by researchers even for what not meant for was Cronbach Alpha [10]. Cronbach Alpha is a reliability estimate meant for data on a continuous scale and for software (such as SPSS, Social Package for Social Science) that uses Pearson correlation matrix and Pearson covariance to determine the estimate. For categorical data (ordinal), it requires software (such as R programming Language for Statistical Computing) that makes use of a tetrachoric/polychoric correlation matrix in determining the estimate [11].

Nevertheless, [12, 13] allude that his coefficient alpha has mainly been wrongly used in measuring constructs involving multiple items in social and behavioural research. Using Cronbach Alpha, some underlying assumptions must be met, including large sample size, unidimensionality of the data, and the uncorrelated error term. Despite these stringent conditions, Cronbach Alpha is still being used by numerous researchers even when the subject of an investigation is ordinal, the sample size is small, and unidimensionality is not ascertained before going ahead with the estimation because they are hard to be determined in practice, especially with educational and psychological scales [13, 14]. This reliability method remains largely used because many young researchers are exposed to the estimate without taking cognisance of other methods that can be explored, and in-depth knowledge of requirements that must be met before it can be used was not adequately documented for researchers to use. Also, establishing assumptions and deciding on data suitability for the analysis was not clearly stated. Where studies revealed other approaches, it is devoid of simplicity for an understanding of many researchers to replicate. Some researchers made an enormous effort for a balanced treatment about the criticism and misapplication of Cronbach Alpha [15, 16]. Mathematically, Cronbach Alpha is expressed as follows:

$$\alpha = \frac{p}{p-1}\left(1 - \frac{\sum_{j=1}^{p} S_{jj}}{\sum_{j=1}^{p}\sum_{k=1}^{p} S_{jk}}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad \text{Equation 1}$$

$$\omega = \frac{\left(\sum_{j=1}^{p} \widehat{\lambda_J}\right)^2}{\left(\sum_{j=1}^{p} \widehat{\lambda_J}\right)^2 + \left(\sum_{j=1}^{p} \widehat{\psi_{JJ}}\right)} \quad \ldots\ldots\ldots\ldots\ldots \quad \text{Equation 2}$$

Where ω is the coefficient, *λj* is the loading of item *j*, $(\lambda j)^2$ is the communality of Item *j* and ψ_{jj} link to the uniqueness.

Ordinal Alpha Reliability (α)

Another reliability estimate examined in this paper was propounded by [5] known as Ordinal Alpha. Ordinal alpha is used for ordinal reliability coefficients rather than non-ordinal reliability coefficients, like Cronbach alpha for the situation that one's data come from measurements based on ordinal response scales such as rating scales or Likert-type response formats (that is an indication of the level of agreement on an item containing five categories; Excellent, Very good, Average, Fair and Poor). Its estimate reliability is more precise and accurate than Cronbach alpha for binary and ordered response categories.

The focus is on examining the performance of Cronbach alpha with other techniques of reliability estimates because it is the most widely used reliability coefficient in the literature, and it is useful to use a familiar scenario as a concrete example. In other words, the rationale for using an ordinal version of a reliability coefficient is not restricted to alpha. Still, it is equally valid for other reliability coefficients, such as coefficient omega [6] or beta coefficient [17]. Ordinal alpha aims to estimate the thresholds and model the observed cross-classification of response categories through the underlying continuous item response variables. Formally, the observed ordinal response for item *k* with *N* response categories, where the response options n = 0, 1, 2, …, *N*-1, is defined by the underlying variable a* such that

$$a_k = n \quad if \quad \tau_n < a_k < \tau_{n+1} \qquad \text{………… Equation 3}$$

Where, τ_n, τ_{n+1} are the thresholds on the underlying continuum, which are typically spaced at non-equal intervals and satisfy the constraint $\infty = \tau_0 < \tau_1 < \ldots < \tau_{n-1} < \tau_n = \infty$. The underlying distribution does not necessarily have to be normally distributed, although it is commonly assumed due to its well-understood nature and beneficial mathematical properties [18]. Succinctly, ordinal reliability alpha may differ from their non-ordinal counterparts because of their scaling assumptions. The non-ordinal coefficients focus on the reliability of the observed scores by treating the observed item responses as if they were continuous. Meanwhile, the ordinal coefficients focus on the reliability of the unobserved continuous variables underlying the observed item responses. In this way, the ordinal alpha is non-parametric reliability alpha in a non-linear classical test theory sense [19].

Greatest Lower Bound (Glb)

In practice, psychometricians often deal with skewed data distribution of the sample. [2] argued that the greatest lower bound (glb) is one of the most powerful estimators of reliability in his number of studies, especially when data is non-normal as reported by [9] from Classical Test Theory assumption (X = T + E) of an inter-item covariance matrix for observed item scores X. It breaks down into two parts: the sum of the inter-item covariance matrix for item true scores T; and the inter-item error covariance matrix E [20]. Greatest Lower Bound is expressed as:

$$GLB = 1 - \frac{tr\,(E)}{\sigma_x{}^2} \qquad \text{……………………….. Equation 4}$$

Where σ^2_x is the test variance and tr(*E*) is the inter-item error covariance matrix trace. It produces better results than Cronbach's alpha. [21] carried out a simulation study to find this estimator's functioning in non-normal conditions or asymmetrical distributions compared to the functioning of Cronbach alpha. It was reported that alpha had unacceptable performance under asymmetrical conditions with their bias percentage greater than 13%. Nevertheless, GLB had better performance even when the skewness of data distribution value was raised to 0.5 and 0.6, respectively.

Guttman Lambda (L_3)

Another alternative method to estimate reliability aside Cronbach alpha is Guttman Lambda [8]. The reliability is estimated by first splitting a test into two halves in a different order as the researcher desire. Then, the covariance between the score's examinees achieved on each half is computed, and the variance of the total test score, which includes both halves, is computed. The overall test reliability will then be calculated with the below expression;

$$L_3 = \frac{4\, Covariance\, (Half\ 1\ scores, Half\ 2\ scores)}{Variance\, (Total\ score\ on\ test)}$$ …………………. Equation 5

However, the above expression can be applied to any split-half, but Lambda generally means the reliability from the split that maximises this coefficient. This is an interesting reliability coefficient because it's easy to understand and less likely to underestimate reliability than Cronbach's alpha.

Revelle's Coefficient Beta (β)

[7] formulated another reliability index named coefficient beta (β), which showed the equal proportion of variance in scale scores accounted for by a general factor under more general conditions than Cronbach alpha (α). It can also be described as an estimate of the lowest or minimum value in gathering possible split-half reliabilities that are averaged to obtain coefficient alpha. Meanwhile, the coefficient alpha will always be greater than the coefficient beta (except in the degenerate and improbable case where all split-half estimates are precisely equal, a situation that [17], defined as "tau equivalence"). To achieve the coefficient of beta, [22] ICLUST function item-clustering procedure should be used with Cronbach's coefficient alpha measure of internal consistency as criteria for judging the dimensionality and internal homogeneity of multiple measured items. Importantly, the beta coefficient is best to use when evident that more than one factor accounted for the variation observed in the responses to the scale. This can be computed using;

$$\beta = \frac{(k+p)^2\, (Min\, \overline{\sigma_{ij}})}{\sigma_c{}^2}$$ ……………………………. Equation 6

where k is the number of items in the first subscale, p = the number of items in the second subscale, minσ_{ij} is the minimum of all possible averages of between-half item covariances, and σ^2_c is the variance of the total scale.

The study of [17] examined the relationships between coefficient alpha and Coefficient beta. Researchers submitted that coefficient beta achieves maximum utility relative to a coefficient alpha when a multidimensional scale has unequal or equal general factor loadings. Though, [7], as claimed by [23] recommended that a value less than 0.50 is regarded as a low coefficient of beta, which represents less than 50% of scale variance associated with a general first factor. Therefore, if the beta is less than 0.50 for any single set of items, the presence of subscales should be investigated.

Software's for Reliability Estimation

Statistical analysis was usually done manually before the advent of a computer. Still, over many decades now, SPSS has been registered in the heart and soul of the researchers and makes it hard to explore other prominent available software. One such is the R programming language (http://www.r-project.org) which is open-source software [24]. The software is available for free with different packages embedded in the library for different analysis, which is downloadable once into a system and can be utilised subsequently. However, the absence of programming/lines of coding knowledge of most researchers have created fear and scared many researchers off from exploring it, rather complacent with SPSS, despite its limitations (that is, the usage of Pearson correlation coefficient severely underestimates the true relationship between two continuous variables when the two variables manifest themselves in a skewed distribution of observed responses) of estimating reliability coefficient of the ordinal scale of measurement correctly. Research has shown that R is more sophisticated and robust than SPSS software to compute reliability coefficient and other analyses [25].

Also, the debates on whether the informational value of point estimates is negligible compared to the value of confidence intervals had been on for quite some time now. It is important to state that SPSS lacks the capability to generate confidence intervals for most of its statistics (reliability output). This may allude to the major reason many researchers only reported point estimates for their reliability coefficient. R made a significant contribution in this regard by providing confidence interval estimates and reliability estimates, which makes the reporting more robust and comprehensive. With new development in using R software to establish modern approaches in estimating reliability, researchers must shift their paradigm from reporting only reliability point estimates without integrating confidence intervals into their report. Consequently, this paper examined the performance of different methods (such as ordinal alpha, coefficient Omega, Guttman Lambda, and Revelle coefficient of Beta) of estimating reliability coefficient for non-cognitive instruments compared to Cronbach Alpha and provide step by step ways of performing estimates via R language in a programming way.

Methodology

Design, Participants, and Measure

The study is a non-experimental design of scale development research type. Respondents were selected using purposive and snowballing sampling methods. Data used was generated from remote administration of the Students Mathematics Engagement Scale questionnaire, N = 883. Respondents' responses to 15 items in a seven-point Likert scale (7- Very true of me, 6- True of me, 5- Somewhat true of me, 4- Neutral, 3- Somewhat untrue of me, 2- Untrue of me and 1-Very untrue of me) were subjected to analysis using R programming language software. The age of the respondents ranged between 12-16 years, with 574 (65%) Males and 309 (35%) Females participating in the study, respectively.

Results

To start with, the latest version of the R and Rstudio software program (4.0.2) needs to be downloaded and installed on the system (This is done on PC, Mac OS or Linux). This software is free open source downloaded without any financial obligation from the website (http://www.r-project.org). R works with a line of codes called a command to execute the results. Therefore, is multi-tasking in doing many analyses with appropriate downloaded add-on packages for each analysis. In this paper, R packages (psych, cocron and userfriendlyscience) are used for reliability estimates of Cronbach alpha, ordinal alpha, omega alpha, Guttman Lambda, GLB and Revelle beta their respective line of codes.

The R and Rstudio Interface

To get underway, double click on the icon of either R or RStudio just as you would open any other application on your computer. After that, the 'R Console' window will pop up on the screen, similar to Figures 1 and 2. Also, you would see a symbol that looks like a greater sign ('>'), which is the R prompt. A line of codes typed after the prompt can be performed by hitting the enter key.

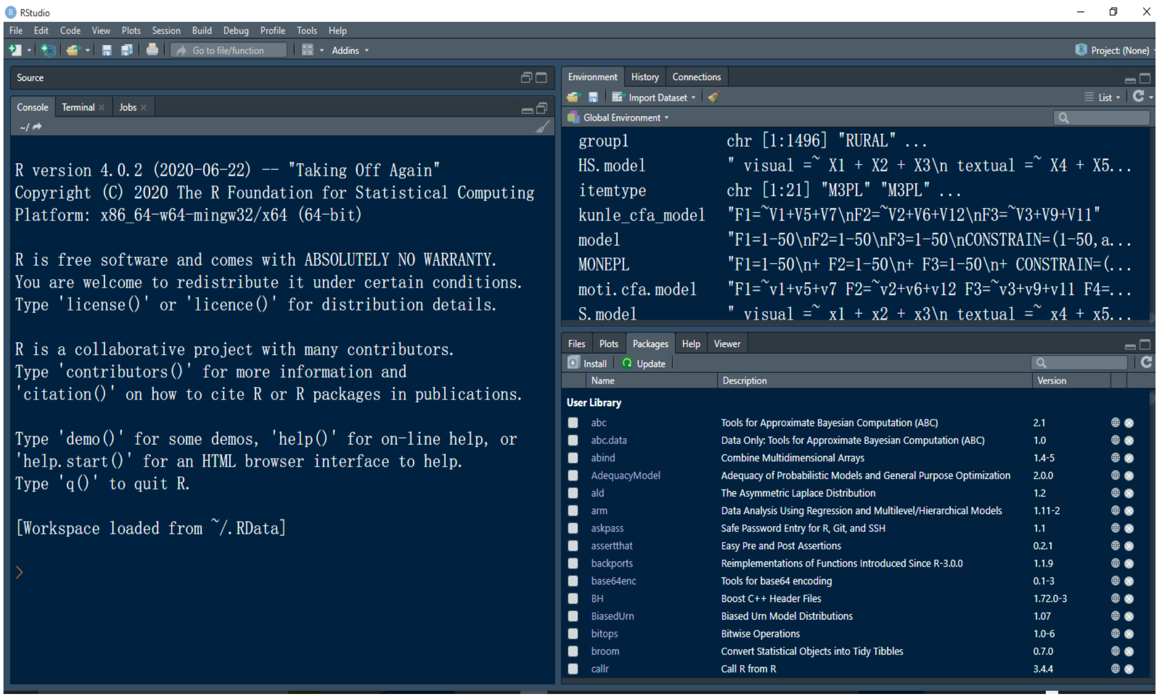

Figure 1: Rstudio User Interface

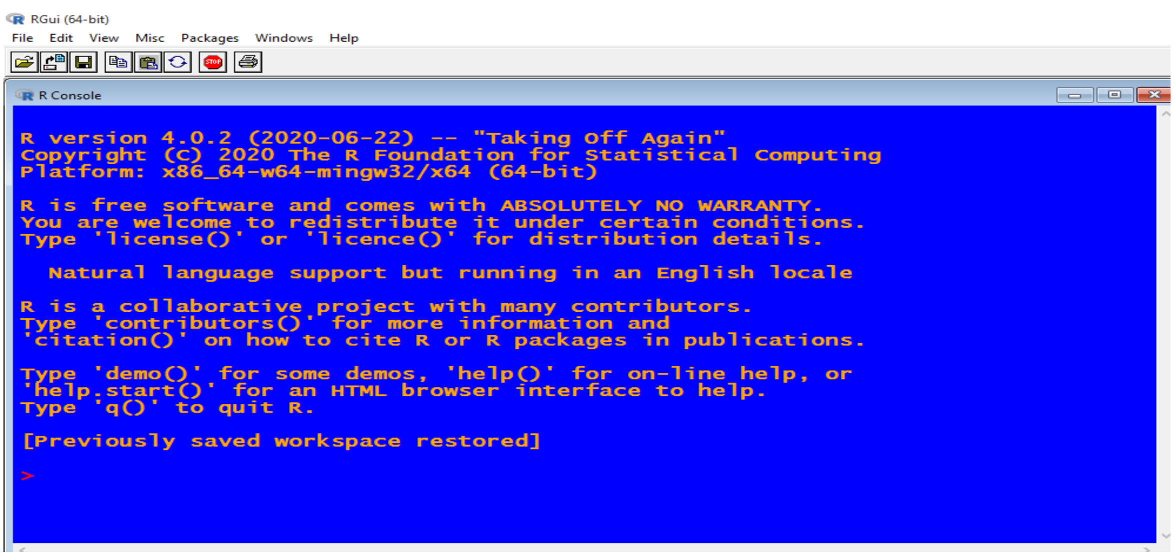

Figure 2: R User Interface

Loading Data into R and Rstudio Environment

The two need either a full path name to be indicated or data files to be in their working directory. The working directory can be configured through menus in the R console or call the getwd () function. More so, the dataset should be formatted into command delimited (.csv) or tab-delimited (.txt) file extension *(Maths_Eng.csv)* and saved on a named created folder on the desktop (for instance; the folder name here is RELIABILITY_ANALYSIS) before the analysis begins. Many R functions take multiple arguments that help them do their job. A function can contain as many arguments as long as each is separated by a comma. The following codes were used to get the working directory and loaded dataset after the prompt >. Note that the arrow used by the symbols <- is an assignment operator.

```
> getwd ( )
> "C:/Users/KunleAyanwale/Desktop/RELIABILITY_ANALYSIS/     Maths_Eng "
> Maths_Engagement <- read.table ("Maths_Eng.csv", sep =",", header = TRUE)
```

Call fix ( ) function to confirm the correctness of the uploaded dataset into the R environment with;

```
> fix (Maths_Engagement)
```

After the dataset has been uploaded correctly, the next is to estimate different reliabilities and examine their performance across the board. This feat is achieved by installing and loading packages specifically created for each estimate. The first package used is called psych [7]. Installing the package requires an internet connection. The installation step is needed the first time you use the package, whereas the library function library ( ) is required in every new R session that you want to compute.

```
> install.packages (“package name”, dependencies = TRUE)
> install.packages ("psych", dependencies = TRUE)
> library (psych)
```

In the psych package, many functions are loaded as part of the package (such as alpha, Omega, Guttman, Mardia, describe, etc.), and bootstrap confidence interval can be obtained for the estimates. Meanwhile, describe function {describe( )} was used to check the descriptive statistics of the dataset (such as n, mean, standard deviation, minimum, maximum, range, skewness, and kurtosis). The output in the R console window should be similar to this:

```
> library(psych)
> x <- describe (data = Maths_Engagement)
> print(x)
```

Table 1

	vars	N	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Eng1	1	883	5.54	1.33	6.00	5.72	1.48	1.00	7.00	6.00	-1.18	1.48	0.04
Eng2	2	883	5.47	1.36	6.00	5.66	1.48	1.00	7.00	6.00	-1.14	1.18	0.05
Eng3	3	883	5.56	1.33	6.00	5.75	1.48	1.00	7.00	6.00	-1.17	1.36	0.04
Eng4	4	883	4.93	1.56	5.00	5.07	1.48	1.00	7.00	6.00	-0.65	-0.15	0.05
Eng5	5	883	4.91	1.59	5.00	5.06	1.48	1.00	7.00	6.00	-0.66	-0.23	0.05
Eng6	6	883	4.68	1.66	5.00	4.80	1.48	1.00	7.00	6.00	-0.50	-0.46	0.06
Eng7	7	883	5.19	1.41	5.00	5.34	1.48	1.00	7.00	6.00	-0.91	0.72	0.05
Eng8	8	883	5.17	1.41	5.00	5.32	1.48	1.00	7.00	6.00	-0.92	0.77	0.05
Eng9	9	883	5.14	1.42	5.00	5.28	1.48	1.00	7.00	6.00	-0.83	0.52	0.05
Eng10	10	883	3.91	1.70	4.00	3.94	1.48	1.00	7.00	6.00	-0.13	-1.00	0.06
Eng11	11	883	4.01	1.77	4.00	4.05	1.48	1.00	7.00	6.00	-0.15	-1.07	0.06
Eng12	12	883	3.84	1.75	4.00	3.84	1.48	1.00	7.00	6.00	-0.03	-1.04	0.06
Eng13	13	883	4.39	1.68	5.00	4.48	1.48	1.00	7.00	6.00	-0.48	-0.66	0.06
Eng14	14	883	4.56	1.68	5.00	4.66	1.48	1.00	7.00	6.00	-0.57	-0.54	0.06
Eng15	15	883	4.53	1.67	5.00	4.61	1.48	1.00	7.00	6.00	-0.54	-0.61	0.06

Next is the function that checked for normality assumption of the dataset called *mardia* tests of multivariate skew and kurtosis. The output will look like a normal Q-Q plot in the R console;

> mardia (data = Maths_Engagement)

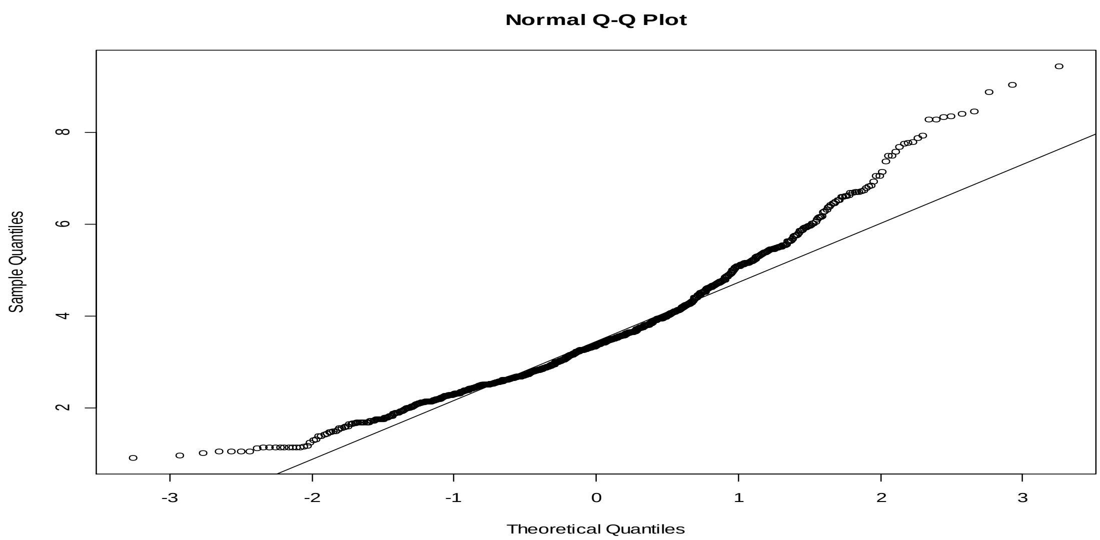

Figure 3: Mardia Multivariate Normality Plot

Figure 3 depicts that the data points drifted from the diagonal line in an apparent non-linear fashion. Then, the dataset was not normally distributed. Also, scree function {scree ( )} presents the scree plot of the eigenvalues for factor analysis and principal component analysis for the dataset (Maths_Engagement). This was further used to check whether the dataset is uni-dimensional or multidimensional.
> scree (data = Maths_Engagement)

Figure 4: Scree plot

Figure 4 suggests that the dataset is multidimensional with evidence of three factors. This is against one of the assumptions datasets for Cronbach Alpha estimate must meet.

Thus, carrying out a diagnosis assessment of the data is crucial. This is what many researchers failed to do. Once the assumption is violated, there is no way the estimates would not be misleading. Next are the commands that estimate ordinal alpha. A polychoric correlation was established using function polychoric ( ), which provides the polychoric correlation matrix for the data = Maths_Engagement. The output looks like this in the R console;

> x <- polychoric (data = Maths_Engagement)
> print (x)

Polychoric correlations

Table 2

Eng1	Eng2	Eng3	Eng4	Eng5	Eng6	Eng7	Eng8	Eng9	Eng10	Eng11	Eng12	Eng13	
Eng1	1												
Eng2	0.82	1											
Eng3	0.85	0.86	1										
Eng4	0.60	0.68	0.69	1									
Eng5	0.60	0.70	0.67	0.91	1								
Eng6	0.55	0.63	0.63	0.89	0.89	1							
Eng7	0.71	0.76	0.77	0.74	0.75	0.73	1						
Eng8	0.67	0.70	0.71	0.71	0.69	0.67	0.82	1					
Eng9	0.68	0.72	0.72	0.72	0.72	0.71	0.83	0.91	1				
Eng10	0.08	0.05	0.08	0.40	-0.02	-0.02	0.07	0.07	0.04	1			
Eng11	0.07	0.03	0.03	-0.04	-0.05	-0.04	0.03	0.02	-0.01	0.86	1		
Eng12	0.04	0.01	0.02	-0.02	-0.04	-0.02	0.03	0.03	0.01	0.84	0.90	1	
Eng13	0.06	0.03	0.06	-0.05	-0.09	-0.06	0.02	0.10	0.30	0.63	0.72	0.68	1
Eng14	0.08	0.05	0.07	-0.03	-0.07	-0.04	0.04	0.03	0.01	0.65	0.72	0.68	0.87
Eng15	0.10	0.06	0.08	-0.02	-0.05	-0.03	0.06	0.03	0.03	0.64	0.70	0.67	0.84
	Eng14	Eng15											
Eng14	1												
Eng15	0.92	1											

The polychoric correlation matrix and tau values were saved in "*Engagement."* In this step, R will not generate any output.

> Engagement <- polychoric (data = Maths_Engagement)

Here, R produces (raw and standardized) alpha, and corresponding item statistics, based on the data set or matrix indicated in brackets. (The $rho command specifies that only the correlation matrix is used for the calculation, disregarding the tau values saved in conjunction with the matrix). From the output generated, *raw alpha* and *std. alpha* connote "*ordinal alpha"* index because it was based on the polychoric correlation matrix for the dataset saved under the name Engagement. The output looks like this in the R console;

> x <- alpha (Engagement$rho)
> print (x)

Table 3

Raw Alpha	Std Alpha	G6 (smc)	Average r	S/N	Median r	Lower	alpha	uper	95% CI
0.90	0.90	0.97	0.37	8.7	0.08	0.86	0.90	0.90	

This command gives the Cronbach's and standardized alpha (Maths_Engagement). R estimated alpha from the Pearson covariance and Pearson correlation matrices of the dataset. Of course, this compares "*Cronbach alpha*" with the earlier estimated "*ordinal alpha"* coefficient. The output looks similar to this in R consoles;

> alpha (data = Maths_Engagement, 'check.keys=TRUE')

Table 4

Raw Alpha	Std Alpha	G6 (smc)	Average r	S/N	ase	mean	0.95	Median	
0.78	0.78	0.86	0.34	7.6	0.0069	4.8	0.90	0.055	

Guttman is another version of ordinal reliability, estimated using a polychoric correlation matrix. In the output, similar estimates are named as beta, Guttman bounds L1, L2, L3 (alpha), L4 (max), L5, L6 (SMC), Ten Berge bounds mu0, mu1, mu2, mu3, alpha of the first principal component (PC), and the "estimated greatest lower bound based on communalities." The output looks like this in the R console;

```
> x <- guttman (Engagement$rho)
> print(x)
Guttman bounds
L1 = 0.84
L2 = 0.92
L3 (alpha) = 0.90
L4 (max) = 0.97
L5 = 0.88
L6 (smc) = 0.97
Ten Berge bounds
mu0 = 0.90 mu1 = 0.92 mu2 = 0.92 mu3 = 0.92
alpha of first PC = 0.92
Estimated greatest lower bound based upon communalities = 0.97
beta found by split Half = 0.25
```

Next is the ordinal version of the reliability coefficients for Omega (hierarchical and total) because their calculation is based on the polychoric correlation matrix of the dataset. After installing a userfriendly science package, many embedded functions (such as scaleReliability, scaleDiagnosis, scaleInspection, and scaleStructure). Here, *scaleReliability* was used because reliability estimates and confidence intervals can be established in one run (such as Ordinal alpha, Omega, Cronbach alpha, GLB). Its output estimates are similar to this in R consoles;

```
install.packages ("package name", dependencies = TRUE)
install.packages ("userfriendlyscience", dependencies = TRUE)
library (userfriendlyscience)
> x <- scaleReliability (data = Maths_Engagement)
> print (x)
Information about this analysis:
Dataframe: Maths Engagement
Items: all
Observations: 883
Positive correlations: 75 out of 105 (71%)
```

Estimates at the ordinal level:
Ordinal Omega (total): 0.88
Ordinal Omega (hierarchical): 0.77
Ordinal Cronbach's alpha: 0.90
Revelle's Omega (total): 0.94
Greatest Lower Bound (GLB): 0.97
Coefficient H: 0.96
Cronbach's alpha: 0.78
Confidence intervals:
Ordinal Omega (total): [0.87, 0.89]
Ordinal Cronbach's alpha: [0.89, 0.94]

Next are the commands that estimate Revelle coefficient beta (β), which use iclust (). This function was part of the psych add-on package and provided item by cluster structure matrix for the data = Maths_Engagement. Also, ICLUST runs the cluster analysis iteratively to improve the quality of the scale and the solution's overall goodness of fit, using item-cluster intercorrelations through a "cluster purification" process [22]. The output is usually generated estimates for Cronbach alpha, Revelle beta, and iclust graph (Figure 5) concurrently and look like this in the R console

> library (psych)
> ICLUST (data = Maths_Engagement)
ICLUST (Item Cluster Analysis)
Original Beta:
C12 C13
0.87 0.83
Cluster fit = 0.97 Pattern fit = 0.99 RMSR = 0.06

ICLUST

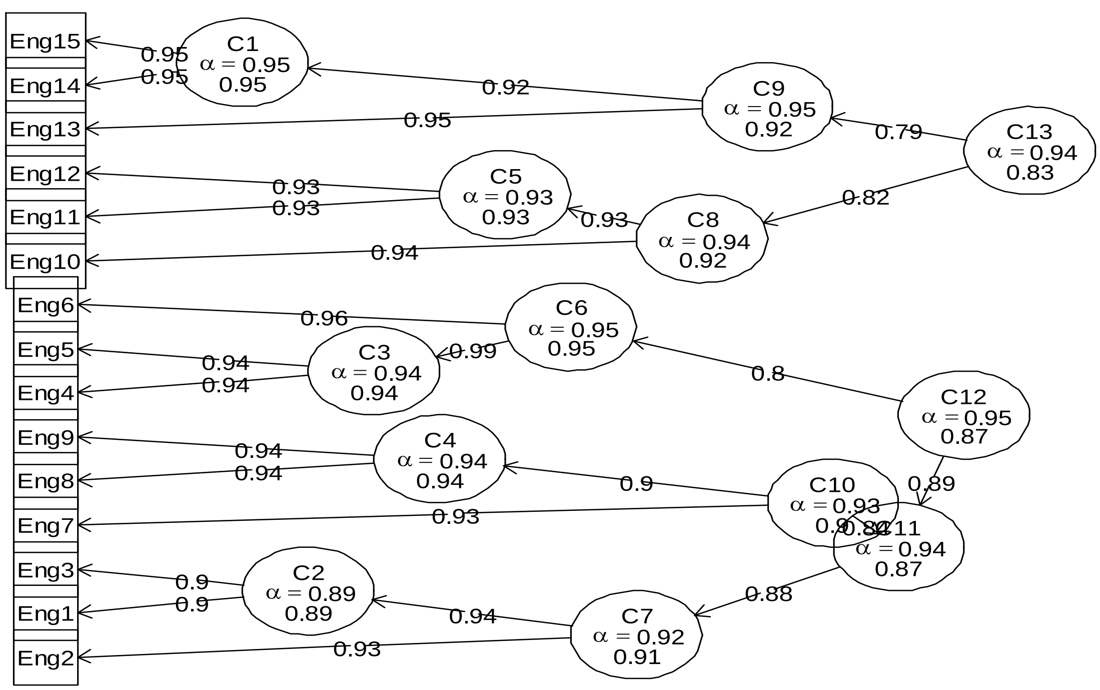

Figure 5: Item Cluster Structure

Figure 5 of ICLUST clustering is a hierarchical tree diagram displaying a set of highly reliable, often correlated (non-orthogonal) factorially homogeneous clusters. The tree diagram also gives additional insights into potential subscale structures within each cluster or scale. The item-by-item growth of a cluster or scale is explicitly mapped with an accompanying set of homogeneity statistics. [23] argued that hierarchical tree representation of item and cluster merges produces specific diagnostic and interpretive information not obtainable using other scales development methods, such as factor analysis or multidimensional scaling. Consequently, it was suggested that the ICLUST technique to scale development provides a twofold advantage. It is a psychometrically coherent method for estimating coefficient beta to better inform judgments about scale homogeneity and provides a more robust and useful method of displaying the internal substructures of scales compared to traditional factor or component analysis.

Table 5

Summary of Reliability Estimates

S/N	N	Number of Items	Approaches	Index	Confidence Interval
1	883	15	Cronbach alpha	0.78	-
2	883	15	Ordinal alpha	0.90	[0.89, 0.94]
3	883	15	Coefficient Omega	0.88	[0.87, 0.89]
4	883	15	Gutmann Lambda	0.90	-
5	883	15	GLB	0.97	-
6	883	15	Revelle coefficient beta	0.87	-

Discussion

Many years back, misuse of Cronbach alpha by researchers had come under serious criticism and debates in many articles due to the reasons of whether multiple item measures obeyed underlying assumptions of the estimation (such as unidimensionality, tau-equivalence, etc.) and how appropriate is the usage of SPSS software for the establishment of an alpha coefficient. This paper examined alternative approaches using R programing language and performance to Cronbach alpha. Findings showed that instruments with an ordinal scale of measurement are vulnerable to multidimensionality (when the underlying factors are more than one). The perfect inter-correlation of items' true score would be affected by this. Furthermore, it was evident from various reliability estimates used that measures of items using Pearson correlation or Pearson covariance matrix would lead to underestimating and the spurious point estimate of Cronbach alpha. Other forms of reliability performed better in their estimation compared to Cronbach alpha. Another remark in this paper was that reporting point estimate for reliability coefficient is insufficient without taking cognisance of confidence interval values into the report. Reporting 95% confidence interval values and point estimate for reliability coefficient would showcase the quality of the measurement instrument and suggest how high the estimate is. Findings from this study corroborate the position of researchers such as [13, 16, 20, 25-27] that other approaches to reliability estimates produced more sensible and better index compared to Cronbach alpha.

Conclusion

It was crystal clear and agreed by researchers that estimation of Cronbach Alpha using SPSS when the instrument measured multiple items is grossly inadequate and rarely apt. However, it remains the most predominant and used statistics by the researchers in the literature because they lack technical know-how on the workability of other better approaches. Other forms of modern approach such as ordinal alpha, Revelle coefficient beta, coefficient Omega, GLB, and Gutmann Lambda produced better and more precise estimates, though their performance differs among themselves. These used the tetrachoric/polychoric correlation matrix to estimate their coefficients and confidence interval, which credence to the measurement instrument via R language. All these were developed to cater for all the shortcomings that characterized assumptions and usage of SPSS for Cronbach Alpha estimation when the instrument is an ordinal scale of measurement. Therefore, it is recommended that researchers explore and shift their paradigm from conventional reliability estimates through SPSS to modern approaches using the R programming language.

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Authors' contributions

Ayanwale, MA: Conceptualisation, writing—original draft preparation, methodology, data curation, data analysis, visualization, discussion and conclusion.

Alasa, VM: Resources, writing—review and editing and supervision.

Oyeniran, DO: Validation, questionnaire administration and references alignment.

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