Development and Factorial Validation of a Scale for Measuring the Causes of Data Fabrication in Education Research Studies in Nigeria

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Abstract: The research focuses on creating and validating the Causes of Data Fabrication Scale (CDFS) to understand the reasons behind data fabrication in educational research. Initially comprising 38 items, the scale was refined to 27 items based on expert input and content validity. Using a sample of 143 educators, the study employed rigorous statistical methods, identifying five key factors contributing to data fabrication: researcher-related issues, institutional factors, respondent influences, funding challenges, and research competence. Despite slight deviations in some item loadings, their significance in literature and expert agreement justified their inclusion. Overall, the study offers a crucial tool for scholars to investigate data fabrication causes, enhancing academic integrity in educational research.

Keywords: Data fabrication, research misconduct, validity, reliability, factor analysis

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Introduction

Researchers must conduct research responsibly since academic integrity is critical to the academic community's foundation and reputation (Rajah-Kanagasabai & Roberts, 2015). The overarching construct underpinning this study is research misconduct, a multifaceted phenomenon encompassing various unethical practices such as data fabrication, falsification, plagiarism, authorship issues, and unethical research conduct. Within this broader landscape of research misconduct, the present study narrows its investigative lens specifically on data fabrication—a practice characterized by the deliberate creation of false or misleading data representations. This focus is predicated on the alarming prevalence and ramifications of data fabrication within academic and research settings, as corroborated by seminal studies (Bouter et al., 2016; Laskar, 2017).

Making up data or findings and reporting them is known as data fabrication. It entails changing data and reporting it as though it were a true depiction of a study that never took place. When a researcher utilizes personal data to fill up an interview schedule or questionnaire, this is known as data fabrication. (Kang & Hwang, 2020). According to researchers, papers have been withdrawn as a result of fabrication (Dal-Ré & Ayuso, 2021; Kuroki, 2018; Nurunnabi & Hassain, 2019). The users of the results are apt to be misled into believing that the study is authentic and dependable when it is not. (Bouter et al., 2016; Freitas et al., 2021; Gaspar & Esteves, 2021; Stacey, 2016). The factors that encourage or make researchers engage in data fabrication need to be investigated. In the field of education, there appears to be no scale to measure the causes of data fabrication. We believe that for the causes of data fabrication to be properly investigated, there is a need to develop a scale on it in the Nigerian setting. The development of a scale on the causes of data fabrication within the Nigerian context holds significant implications for academic rigor, societal trust, and economic competitiveness. Academically, these courses act as safeguards against the compromise of research integrity by equipping scholars with the skills necessary to identify and mitigate fraudulent practices in data collection and analysis. Societally, they promote transparency and accountability, thereby reducing the potential for skewed perceptions and misguided policy decisions. Economically, the accuracy and reliability of data are essential for Nigeria's position in the global marketplace, influencing investment attractiveness and sustainable growth prospects (Omumu et al., 2022). Thus, the imperative for such educational initiatives transcends mere academic concerns, fostering a culture of integrity, innovation, and societal impact within a rapidly evolving research landscape.

There are several surveys and questionnaires on assessing researchers' misconduct. Some of them addressed the prevalence of research misconduct (Broome et al., 2005; Hadji et al., 2016; Khadem-Rezaiyan & Dadgarmoghaddam, 2017; Rankin & Esteves, 1997; Shamsoddin et al., 2021) and publication pressure (Tijdink et al., 2014). The Persian research misconduct questionnaire (PRMQ) consisted of 63 items. A section of the questionnaire concentrated on why researchers engaged in research misconduct (Shamsoddin et al., 2021). Khajedaluee et al. (2019) questionnaire contained 75 items that assessed norms and attitudes towards plagiarism. A 5-point scale containing 60 research misbehaviours was used by Bouter et al. (2016) to identify the frequency of occurrence, preventability, impact on truth (validity), and impact on trust among scientists on the research misbehaviours listed in the questionnaire. All the scales used in these studies focused on research misconduct and were interested in finding out the levels of prevalence of research misconduct. Research misconduct includes data fabrication, falsification, plagiarism, authorship issues, unethical research, etc. There is need to have a clear understanding of each of these components of research misconduct. A scale that focuses solely on measuring the causes of data fabrication is needed to understand data fabrication issues properly. In addition, most of the work on research misconduct was done in the medical field (Ghajarzadeh et al., 2013; Poutoglidou et el., 2022; Shamsoddin et al., 2021). Data fabrication can negatively affect the medical field and also affect other areas, including the education sector.

The pertinence of this study gains heightened significance within the Nigerian context, where empirical investigations into the causative factors and implications of data fabrication remain conspicuously scant. Despite the burgeoning academic landscape in Nigeria, characterized by increasing research endeavours and scholarly outputs, there exists a palpable lacuna in comprehensive assessments of data fabrication within educational studies. This lacuna is not merely an academic oversight but engenders profound implications for academic integrity, societal trust, and economic competitiveness within the Nigerian milieu.

The urgency of investigating data fabrication within Nigeria is further exacerbated by global trends and empirical evidence highlighting its detrimental effects on research integrity and credibility. While extant literature offers invaluable insights into research misconduct, including data fabrication, most of these studies are situated within Western contexts, predominantly in the medical field. Consequently, there exists a conspicuous gap in understanding data fabrication dynamics within diverse socio-cultural and academic landscapes, particularly within the educational sector in Nigeria.

Hence, the primary objective of this study is to develop and factorial validate a scale specifically tailored to measure the causes of data fabrication within educational studies in Nigeria. By elucidating the underlying factors precipitating data fabrication, this study aspires to furnish the academic community with a robust instrument for critically examining and mitigating this pervasive malfeasance. This study seeks to develop and validate a new scale to measure the causes of data fabrication in education studies in Nigeria. The study describes the underlying factors found within the scale. A scale that measures the causes of data fabrication could help the research environment to examine data fabrication more critically and provide cues on ways to eliminate it. The scale will help education researchers in developing countries to measure the causes of data fabrication in their respective environment. In this study we present a brief explanation on the procedure used in the initial development of the 'Causes of data fabrication scale' (CDFS). The psychometric properties of the scale were discussed in detailed.

Method

The current study is part of a broader project. Figure 1 shows an overview of the processes utilized, which is similar to the one used by Goh and Blake (2021).

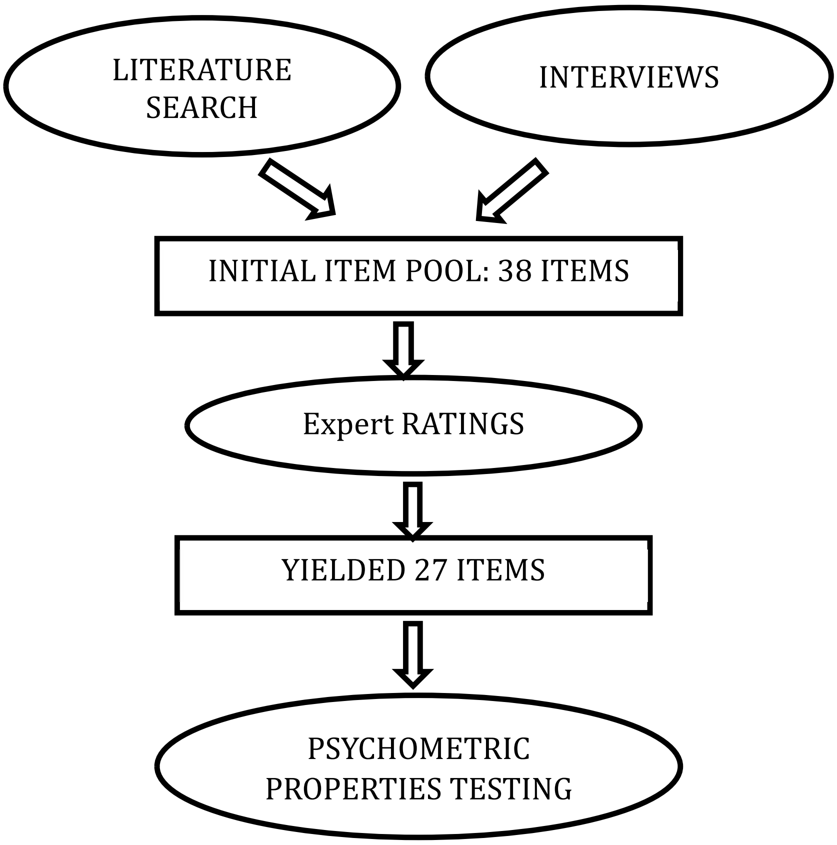

Figure 1: Procedure applied for the study

1. *Scale Development*
   Literature Review

First, we carried out a literature review on data fabrication scales. Secondly, we conducted interviews. Initially, we embarked on an exhaustive literature review encompassing extant scales and scholarly works focused on data fabrication within academic settings. This comprehensive review served as a foundational framework for conceptualizing our research methodology and contextualizing the phenomenon of data fabrication.

One university and one college of education was used for the interview process. From the faculty of education in the university and the school of education in the college of education, we selected 15 academic staff using convenience sampling technique. Ten of them were from the faculty of education and five were from the school of education. The interviews were semi-structured, allowing for a flexible yet focused discourse that facilitated the exploration of participants' perspectives on data fabrication. This approach enabled us to maintain a semblance of structure while affording participants the latitude to articulate nuanced insights and experiences. The interviews were conducted by a team of trained researchers well-versed in qualitative research methodologies. Each participant engaged in a single interview session, conducted in a formal setting conducive to open dialogue and intellectual exchange. The interview protocol comprised a multi-dimensional array of questions designed to elicit diverse insights. The format encompassed basic descriptive queries, experiential narratives, follow-up probes, and comparative analyses, as delineated by Alordiah et al. (2023) and Ghayas et al. (2022), to facilitate a comprehensive exploration of the factors precipitating data fabrication among academic staff. After the interviews, trained transcribers meticulously transcribed the recorded responses verbatim. The transcripts were then subjected to a rigorous qualitative data analysis, specifically employing the method of constant comparison as elucidated by Alordiah et al. (2023). To explicate the process of thematic analysis, we meticulously followed the guidelines delineated by Falaye (2018). Initially, individual responses were coded to capture singular ideas or concepts. Subsequently, codes manifesting analogous themes or ideas were systematically clustered to formulate categories. Interrelated categories merged into main themes that captured the predominant factors contributing to data fabrication among academic staff within the selected institutions.

With the information from the literature review and the results from the thematic analysis we developed a 38-item scale. As much as possible we retained the words and phrases from the interview data. Expert rating of the 38 items was done. Twenty-two respondents were selected through purposive sampling techniques to take part in the rating exercise. These 22 respondents consist of experts in scale constructions and senior faculty offices. We sent the new scale to them through email/WhatsApp. The respondents were asked to determine the importance (very important=4, important=3, somewhat important=2, and not important=1) and adequacy (very adequate=4, adequate=3, slightly adequate=2, and not adequate=1) of the scale's items. The number of items in the scale was reduced to 27 based on the responses of the experts. It was the 27 items retained in the Causes of data fabrication scale (CDFS) that was subjected to item analysis to determine the psychometric properties of the scale.

2. Procedure for Psychometric Properties Testing

In order to provide the psychometric properties of the new scale the following steps were taken. Two studies were conducted to present the psychometric properties of the new scale. In the first study we employed Principal Component Analysis. It was used to establish the factor structure of the new scale. The second study was later done to confirm these factors. Different samples were used for each of the studies.

3. Participant

First study- Principal Components Analysis (PCA)

The participants in this study are lecturers in education at Delta State universities and colleges of education. Delta State has five universities and three colleges of education. Only two of the universities provide education programmes. As a result, the study's participants were confined to the state's two universities and two colleges of education. Random sampling was used to select 50 lecturers from each of the two universities and 30 lecturers from each of the two colleges of education. A total of 160 education lecturers were included in the study. However, due to the response rate on the CDFS, the sample size was reduced to 143 lecturers. There were 85 female lecturers (59.44 %) and 58 male lecturers (40.56 %) in the sample. The number of university lecturers was 93 (65.04 %), whereas the number of lecturers from colleges of education was 50 (34.96 %). Over 52% of the lecturers were PhD holders. We used the sample for the PCA.

Second study- Confirmatory Factor Analysis (CFA)

The participants were drawn from the same universities and colleges of education used for the first study. However, we excluded the lecturers that took part in the first study. A total of 157 lecturers were sampled but only 139 of them returned their questionnaire. Among which were 72 (51.79%) females and 67 (48.21%) males. This sample was used to conduct the CFA.

4. Instrument

The instrument for this study is the "Causes of data fabrication scale" (CDFS). It contains 27 items. Each item was responded to in one of the options provided: strongly agree (SA) with three points, agree (A) with two points, disagree (D) with one point, and strongly disagree with zero point. This instrument was used for both the first and second study.

5. *Procedure for Data collection*

The survey was administered to the participants by research assistants. First and foremost, we sought permission from the faculties/schools of education at the institutions we used. The questionnaire took the participants approximately 10 minutes to complete. The research assistants advised the participant that completing and submitting the questionnaire implied informed permission to participate in the study.

6. *Data Analysis*

The SPSS and R software was used for all statistical analyses. The test for sample adequacy analysis was done first. We carried out a principal component analysis with varimax rotation. It was done to identify the components that existed in the data. A confirmatory factor analysis was done to authenticate the factor structure and provide evidence of scale reliability and validity (Goh & Blake, 2021; Rajah-Kanagasabai & Roberts, 2015). Structural equation modelling was also done to validate the outcome. To estimate the fit of the models, several fit indices – the ratio of chi-square to its degrees of freedom (χ^2/df), the comparative fit index (CFI) the Turker-Lewis fit index (TLI), and the root mean square error of approximation (RMSEA) –were used. To have a good fit, these indices should have values of less than three for the χ^2/df, above 0.90 for CFI and TLI, and below 0.06 for the RMSEA (Alordiah & Chenube, 2023; Goh & Blake, 2021; F. Hair Jr et al., 2014).

Results

1. *Sample adequacy and Model fit*

The Kaiser-Meyer-Olkin (KMO) measure of sample adequacy index was conducted and presented an index of 0.83. The second test, Barlett's test of sphericity, had a significant result of $\chi^2 = 2971$, $p<.001$. These two indicators showed that the sample and correlation matrix were within an acceptable range for the analysis.

2. *Content validity*

The findings revealed that all the items in the CDFS covered up to 65.30% of the domain of the attribute “Causes of data fabrication in educational studies”. The cumulative eigenvalue of 65.30% item coverage of the unidimensionality trait of CDFS is above 50%. Therefore, the CDFS has content validity (Alordiah, 2019).

3. *Underlying factors and item loading*

Five underlying factors can explain 65.30 % of the item variation with an eigenvalue larger than one (See Table 1 and Figure 2). The ‘Researchers factor’ representing the curses related to the researchers was the top factor, accounting for 18.69 % variation. The second factor was titled ‘Institution factor’, and it explained 18.23% of the overall variation. This factor assesses the causes of data fabrication concerning the researcher's institution, the society and journal to which he is submitting the work, and the government. The third factor, the ‘respondents factor’, explained 13.87 %. It examined the variables that led to researchers fabricating data due to respondents’ and research assistant’s activities. The fourth factor, dubbed the ‘funding/resources factor’, explained 7.43 % variations. It asked the researchers about the causes of data fabrication that is related to availability of funds and resources. The fifth and final factor, ‘research competency’, assesses the reasons for data fabrication due to the researcher’s knowledge of the research process.

Table 1: Pattern/structure coefficients of items contained within each underlying factor and their score-reliabilities

Code	Indicator Statement	Factors					Reliability	
		1	2	3	4	5	α	ω
Factor 1	**Researchers factor**						.813	.819
RF1	Laziness on the part of the researcher	.360						
RF2	The heavy workload of the researcher	.620						
RF3	The desire to have fame	.735						
RF4	The habit of always wanting to succeed through illegitimate means	.573						
RF5	The desire to acquire promotion	.450						
RF6	The desire for monetary reward	.568						
RF7	The attitude of always wanting to cut corners	.619						
Factor 2	**Institution factor**						.812	.829
I1	Publish or perish syndrome (pressure on researchers to publish)		.261					
I2	Impact factor stress		.604					
I3	Lack of restraining by the researcher institution		.719					

Code	Indicator Statement	Factors 1	2	3	4	5	Reliability α	ω
I4	Lack of institution policies to tackle scientific misconduct		.762					
I5	Unavailability of equipment/materials/facilities to carry out the research		.704					
I6	Article reviewers/journal owners are requesting non-realistic additional information		.600					
Factor 3	**Respondent factor**						.771	.773
R1	Lack of willingness of the respondents to take part in the research			.560				
R2	It is not easy to have access to the respondents			.615				
R3	Low remuneration to fieldworkers/research assistance			.580				
R4	The pressure placed on research assistance/fieldworkers to meet the deadline			.627				
R5	The respondent attitude of faking their responses (not stating issues exactly the way it is)			.570				
Factor 4	**Funding/Resources**						.855	.859
F1	The limited time to carry out data collection				.706			
F2	Insufficient funds to complete the research				.753			
F3	Poor funding of research by funding agencies				.693			
F4	Competition for grants				.694			
F5	Lack of resources for proper data collection				.613			
Factor 5	**Research competency**						.804	.808
P1	Inability to prepare a standardized questionnaire					.556		
P2	The researcher is not grounded in the research process					.644		
P3	Inability to administer research instruments					.611		
P4	Lack of management skills to handle the process of data collection					.661		
	FACTOR 1	1						
	FACTOR 2	.868	1					
	FACTOR 3	.826*	.690*	1				
	FACTOR 4	.828*	.685*	.907*	1			
	FACTOR 5	.907*	.784*	.759*	.841*	1		

α = Cronbach's α, ω = McDonald's ω, *$p < 0.01$

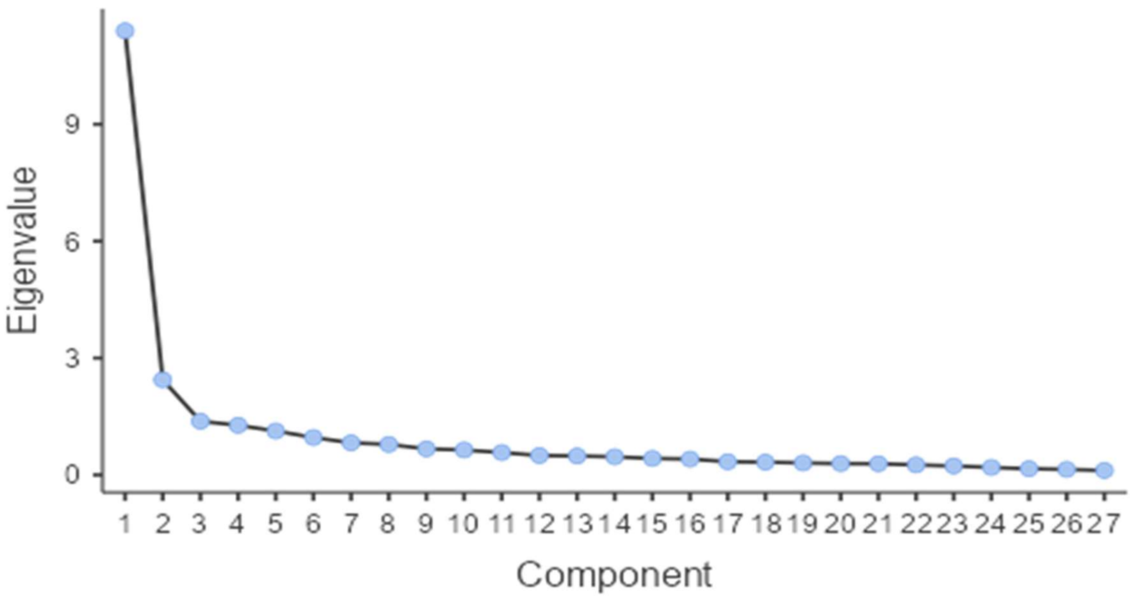

Figure 2: Scree plot for CDFS

Factor 1 contains seven items, Factor 2 contains six items, and Factor 3 contains five items. Factors 4 and 5 were loaded with five and four items, respectively. A typical criterion was an appropriate factor loading equal to or higher than .35. (Meza & González, 2020). All the items loaded above .35 except for the first item in Factor 2 (.26). The item correlation of this item with the other items in factor two was examined. The correlation ranges from .12 to .33 (see Figure 3). It was considered as ranging between mild and moderate. Also, the correlation was significant at .001.

4. Construct validity

The rotated factors loading vary from 0.36 to 0.76 was significant at $\alpha<.001$ except for the first item in factor 2 (see Table 2). These values indicate that the items in the scale were related and contribute to the construct being measured. Therefore, the CDFS has significant construct-related validity (Alordiah, 2019).

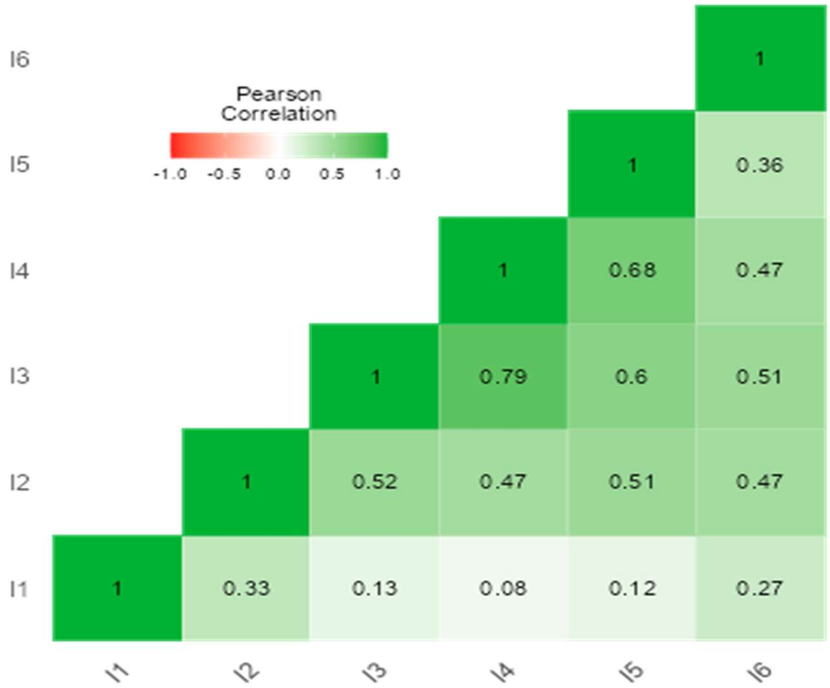

Figure 3: Correlation Heatmap of factor two

5. *Reliability*

All variables have a substantial positive reliability, with values ranging from .685 to .907 (Table 2). These correlations indicate unidimensionality of the scale. Finally, Cronbach's alpha and McDonald's omega coefficients were used to calculate the internal consistency reliability of each component. The coefficients derived from both approaches are consistent, indicating that the sample has a high level of reliability. Factor 4 (Funding/resources) has the highest reliability (.859). Factor 3 has the lowest reliability (.771) (Respondent factor). Table 2 contains the complete results for the internal consistency of the factors.

6. *Second study- Confirmatory Factor Analysis*

All the fit statistics indicated an acceptable model fit of the data (Goh & Blake, 2021). See Table 2.

Table 2: *Model fit for CDFQ*

Model	**Model fit**			
	χ^2/df	CFI	TLI	RMSE
Measurement model	2.89	0.93	0.91	0.058
Structural model	2.82	0.93	0.91	0.057

Table 2 presents the model fit indices for the CDFQ, which was assessed using Confirmatory Factor Analysis (CFA). CFA is a statistical technique used to evaluate how well the observed data fit a hypothesized measurement model. The first set of results pertains to the measurement model. For $\chi 2/df$ (Chi-square to degrees of freedom ratio), a value of 2.89 indicates that for each degree of freedom in the model, there is a chi-square value of 2.89. Typically, values less than 3 are considered indicative of a good fit, suggesting that the observed data align reasonably well with the model's expectations, despite the chi-square being statistically significant. The CFI value of 0.93 slightly exceeds the commonly recommended threshold of 0.90, indicating a good fit of the model to the data (Alordiah, 2022). The CFI compares the fit of the hypothesized model to a baseline model, with higher values suggesting better fit. Similarly, the TLI value of 0.91 also surpasses the acceptable threshold of 0.90, further corroborating that the model fits the data adequately. TLI, like CFI, evaluates the fit of the model concerning a null or baseline model. With a value of 0.058, the RMSE falls below the recommended threshold of 0.08, indicating a close fit of the model to the data. RMSE provides an index that measures how well the model fits the population covariance matrix.

The second set of results relates to the structural model, which goes beyond the measurement model by also considering relationships between latent variables or factors. The $\chi 2/df$ value of 2.82, which is slightly lower than that of the measurement model, continues to suggest a reasonably good fit to the data. Consistent with the measurement model, the CFI remains at 0.93, signifying a robust fit. The TLI also maintains its value at 0.91, supporting the adequacy of the structural model. With an RMSE of 0.057, the structural model continues to demonstrate a close fit to the observed data. Both the measurement and structural models exhibit favourable fit indices, suggesting that the hypothesized models align well with the observed data. These results offer empirical support for the validity and reliability of the CDFQ as a measurement instrument, indicating its suitability for subsequent research applications or theoretical investigations.

7. *Model*

Figure 4 displays the confirmatory factor analysis of the measurement model, revealing that the CDFS is described by five factors retrieved using principal component factor analysis. The items loading on the same factors they loaded on in Table 2.

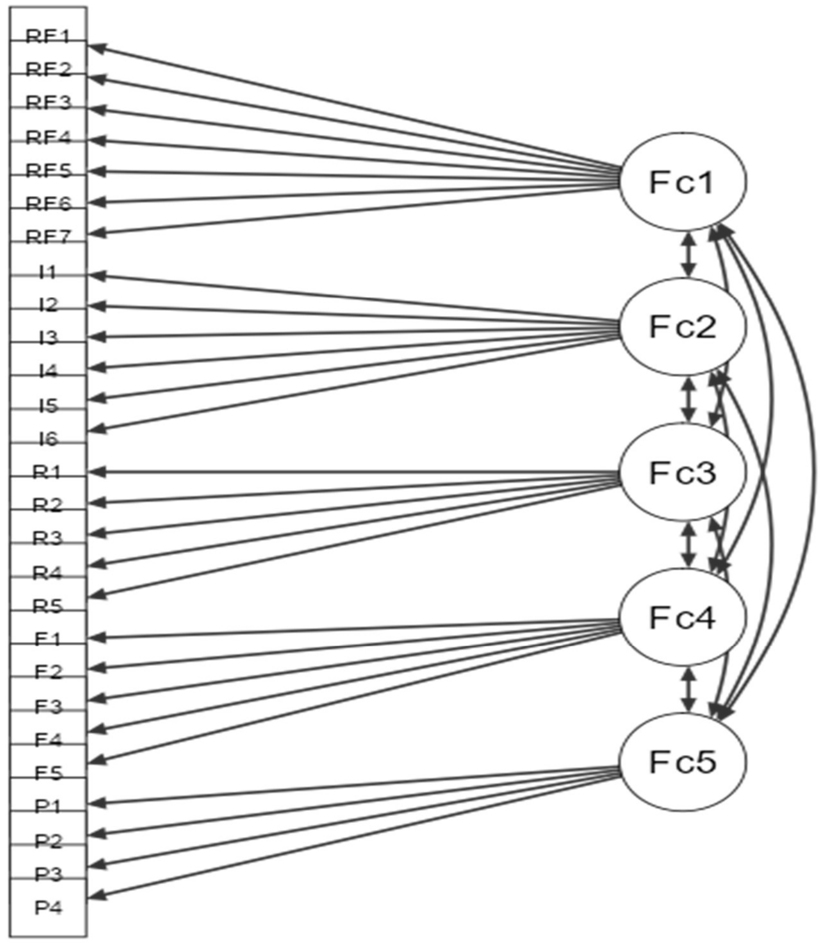

Figure 4: Measurement model

Note: Circles represent factors, rectangle represent observed variables/items, Fc1= Researchers factor, Fc2= Institution factor, Fc3= Respondents factor, Fc4= Funding/resources, Fc5= Research competency

Figure 5 shows a final structural equation model with standardized coefficients on the structure routes after confidence in the measurement model has been established. Because of the recognized degree of fit based on CFI, TLI, and RMSEA indices, the measurement model (Figure 4) and structural model (Figure 5) are accepted (see Table 2). Furthermore, all of the items significantly loaded on the corresponding latent construct.

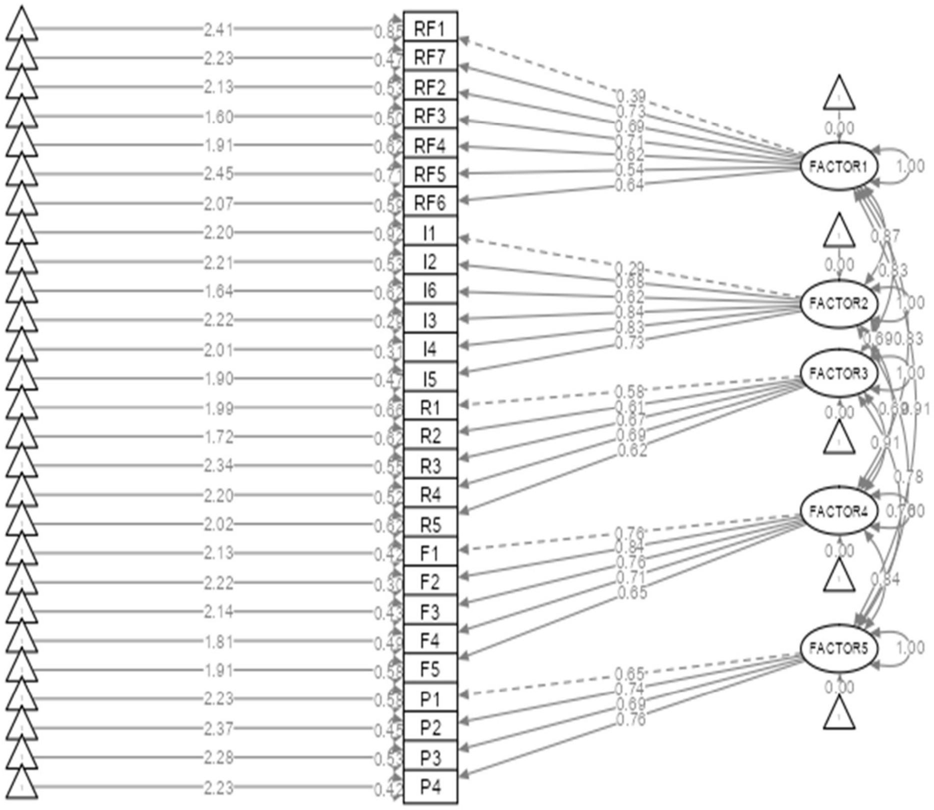

Figure 5: Structural equation model of CDFS
Note: Ellipses represent factors, rectangles represent items, triangles represent error variance.

Discussion

The goal of this study was to develop and validate a scale – namely, the Causes of Data Fabrication Scale – for determining the causes of data fabrication. According to the literature review (Broome et al., 2005; Hadji et al., 2016; John et al., 2012; Khadem-Rezaiyan & Dadgarmoghaddam, 2017; Khajedaluee et al., 2019; Rankin & Esteves, 1997; Shamsoddin et al., 2021), some scales measured the prevalence and causes of research misconduct but there seem to be no scale that solely measured the causes of data fabrication. The preliminary instrument was made up of 38 items. Expert judges were used to determine the proposed instrument's content validity and the appropriateness and relevance of the items. The number of elements on the scale was reduced to 27 based on their reports.

The 27 items and five factors were examined for construct validity using principal component factor analysis and confirmatory factor analysis. The suggested scale had five factors: a) Researchers factor (7 items), b) Institution factor (6 items), c) Respondents factor (5 factors), d) Funding/Resources (5 items), and e) Research Competence (4 items). The correlations between factors 1 to 5 suggest that the various parts of the scale for data fabrication causes are associated. This finding implies that the five factors contributing to the data fabrication scale have a significant relationship (Meza & González, 2020). It is an indication that all the factors are measuring the same construct but from several directions. The item 'Publish or perish' syndrome loaded into factor 2 with a factor loading of (.26) which was below the benchmark of .35 used for this study. However, we decided to retain this item because of its relevance as stated in literature (Bouter et al., 2016; Tijdink et al., 2014) and the reports of the expert judges. This item can be addressed in future studies.

Although the suggested scale appears to have good content and construct validity, researchers must continue evaluating and contrasting its use in different populations and circumstances while also including independent criterion validity and stability reliability assessments. As a result, the suggested instrument would enable researchers to look into the causes of data fabrication in many areas of education. Second, postgraduate, undergraduate, and free-license education researchers can be evaluated based on their perceptions of data fabrication causes. This scale can also be adjusted to fit various fields of study. These are only a few ways the suggested scale can be used.

While the sample was sufficient to validate the instrument, the sample did not sufficiently cover Nigeria, which is one of the work's shortcomings. Private universities were not included in the sample. It was limited to two universities and two colleges in Delta State, Nigeria. Replicating the study on a broader sample, including postgraduate, undergraduate, and free license researchers is necessary. A further in-depth investigation can be conducted to determine the complexity and discrimination level of the scale's items. Adopting the item response theory model to the scale will aid in improving the scale's validity.

Conclusion

The purpose of this research was met, as an instrument that yields a reliable and valid score-measure for the causes for data falsification in education was developed. As a result, the study has helped close a knowledge gap that occurred in prior studies. To put it simply, researchers need an instrument that will allow them to accurately and reliably detect the causes of data fabrication. This idea is a significant step forward in searching for the root causes of data fabrication in educational research.

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