

Strengthening Construct Validity in Psychological and Educational Measurement: A Theoretical Review of Exploratory and Confirmatory Factor Analysis

Dr. Fadila Maatoug

Mohamed Boudiaf University of M'Sila, M'Sila, Algeria

Email: fadila.maatoug@univ-msila.dz

ORCID: <https://orcid.org/0009-0003-8353-4568>

Abstract

Purpose: This study examines the role of factor analysis in establishing the construct validity of psychological and educational measurement instruments. It reviews the conceptual foundations, objectives, principal forms, and methodological procedures of factor analysis, with particular emphasis on the complementary functions of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Design/methodology/approach: The study adopts a theoretical and analytical review approach. Relevant psychometric and methodological literature is synthesized to explain how factor analysis contributes to identifying latent constructs, evaluating dimensionality, refining scale items, and testing theoretically specified measurement models. The review distinguishes the exploratory function of EFA from the hypothesis-testing function of CFA and considers their appropriate sequential use in instrument development and validation.

Findings: Factor analysis provides essential evidence concerning the internal structure of psychological and educational scales. EFA enables researchers to investigate the number and composition of latent dimensions without imposing a fully predetermined model, whereas CFA evaluates whether an explicitly hypothesized measurement structure is consistent with empirical data. Their rigorous application improves item selection, dimensional clarity, theoretical coherence, and the interpretability of test scores. However, valid conclusions depend on appropriate sampling,

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theoretically justified analytical decisions, suitable extraction and rotation procedures, transparent reporting, and the avoidance of validating an exploratory structure solely with the same dataset from which it was derived.

Research implications: Evidence derived from factor analysis should be interpreted as one component of a broader construct-validation process rather than as definitive proof of validity. Future scale-development research should integrate evidence concerning internal structure with theoretical justification, reliability, relationships with external variables, measurement invariance, and the consequences of score interpretation.

Practical implications: Researchers and practitioners should employ EFA and CFA as complementary but methodologically distinct procedures. Whenever feasible, exploratory and confirmatory analyses should be conducted using independent samples or appropriately partitioned datasets. This practice reduces overfitting and strengthens the generalizability of the proposed factor structure.

Originality/value: The study presents an integrated account of factor analysis as a theory-driven psychometric process rather than a purely statistical data-reduction technique. It clarifies the distinct evidential contributions of EFA and CFA and demonstrates how their appropriate use strengthens the scientific quality of psychological and educational measurement.

Keywords: Factor analysis; Exploratory factor analysis; Confirmatory factor analysis; Construct validity; Psychometric validation; Scale development; Educational measurement

Introduction

The construction of psychological and educational scales and the evaluation of their psychometric properties constitute fundamental pillars of scientific research in the human sciences. The accuracy of results and the validity of conclusions depend on the measurement tools possessing high levels of validity and reliability. Construct validity is considered one of the most important types of validity, as it reflects the extent to which a scale measures the theoretical construct or psychological trait for which it was designed; this necessitates the use of advanced statistical methods to verify the quality of the instrument's factor structure.

Among the statistical methods most frequently employed in this field, factor analysis stands out as a key multivariate statistical technique. It aims to uncover the underlying structure explaining the relationships between variables or scale items by reducing a large number of variables into a smaller set of factors representing the fundamental dimensions of the construct being measured. Worthington and Whittaker (2006)

Effective scale development requires integrating theoretical foundations, expert judgment, exploratory factor analysis, and confirmatory validation (Worthington & Whittaker, 2006). Furthermore, factor analysis has become an indispensable tool for developing psychological and educational scales, validating them, and enhancing their psychometric properties—particularly regarding construct validity. Construct validity is established through accumulating evidence that supports the theoretical interpretation of test scores (Cronbach & Meehl, 1955). For Clark & Watson, (2019), construct validity depends on the systematic development of measurement instruments that accurately represent the intended psychological construct

Factor analysis is divided into two main types: Exploratory Factor Analysis (EFA), used to explore the factor structure of an instrument without assuming a prior theoretical model; and Confirmatory

Factor Analysis (CFA), used to test the extent to which actual data fit a pre-hypothesized theoretical model. Both types play a complementary role in the construction and evaluation of measures: exploratory analysis helps identify the number of factors and their dimensions, while confirmatory analysis tests the validity and suitability of this factor structure regarding the data, thereby strengthening the evidence supporting the measure's validity.

In light of the rapid evolution of psychological and educational measurement methods, there has been an increasing reliance on factor analysis. It serves as a scientific approach that provides precise empirical evidence regarding the validity of measurement instruments, assists researchers in refining items and verifying their representation of theoretical dimensions, and enables the assessment of factor model quality using objective statistical indicators. Consequently, employing factor analysis in accordance with sound methodological procedures is essential for ensuring the quality of measures and enhancing confidence in the findings of psychological and educational studies.

Against this backdrop, this theoretical review aims to highlight the role of factor analysis in enhancing the validity of psychological and educational measures. It does so by examining the concept, objectives, and types of factor analysis, and by demonstrating its importance in verifying construct validity. Furthermore, it outlines the procedural steps involved in using factor analysis to assess the validity of such measures, in alignment with modern scientific standards for the construction and evaluation of measurement instruments. Consequently, the research problem can be formulated as follows: What are the procedural steps of factor analysis for assessing the validity of psychological and educational measures?

Factor Analysis

Factor analysis is one of the most important multivariate statistical methods used in psychological and educational sciences. It aims to uncover the underlying structure that explains the relationships among a set of interrelated variables. It is divided into two main types: Exploratory Factor Analysis (EFA), used to discover latent dimensions without imposing a prior model; and Confirmatory Factor Analysis (CFA), used to test the fit of a pre-specified theoretical model against actual data. Together, these two methods contribute to the construction of scientific measures and the assessment of their construct validity, thereby enhancing the quality of research and the accuracy of result interpretation (Abdul Rahman, 2010).

Objectives of Factor Analysis

Eysenck (1953) identified three fundamental objectives for factor analysis—objectives shared by any branch of statistics—which are linked to three perspectives on the nature of factors, as well as numerous methods for factor extraction and rotation. These objectives are:

- 1-Description
- 2-Hypothesis testing
- 3-Generating hypotheses from raw data

Tighza (2012) posits that factor analysis seeks to uncover a relatively small number of unobserved—or latent—variables that adequately represent the interrelationships among a large number of measured or observed variables. In this framework, each latent variable accounts for a portion of the variance or shared information among several measured variables, with the correlation matrix serving as the starting point for the analysis.

Types of Factor Analysis

Tighza explains that Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) are used to determine the psychometric properties—specifically reliability and validity—of scales, tests, and various data collection instruments. Factor analysis is considered a precise method for assessing the reliability and validity of such measures; both EFA and CFA are employed as data analysis strategies falling under the umbrella of multivariate statistical analysis techniques (Tighza, 2012).

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) primarily aims to represent the information contained in a large number of items by linking them to a smaller number of factors or components; in other words, it involves reducing the number of items by grouping them into a few key dimensions without losing a significant amount of the information organized within the original items (Stevens, 2002). To determine the significance of the factors dominating or driving the sample's responses to the instrument, methods are employed to identify which important factors should be retained and which unnecessary ones should be excluded from the analysis—such as the eigenvalue-greater-than-one criterion and the use of the scree plot.

After identifying the significant factors within the hypothesized structure of the measured trait, factor rotation is employed to achieve the principle of "simple structure." This principle implies that each factor exhibits high loadings on a specific subset of variables and low loadings on the others, while each variable loads highly on only one factor and lowly on the remaining factors. Orthogonal rotation methods, such as Varimax, are among the techniques used for this purpose. To label and describe the significant factors as key components of the target trait's hypothesized structure, the extent of the instrument items' factor loadings is examined; the most commonly used threshold in psychological and educational studies is an absolute value of 0.30 (Field, 2007).

2/ Confirmatory Factor Analysis (CFA):

Confirmatory Factor Analysis (CFA) is a significant and powerful statistical method for examining the nature of relationships among various latent constructs. Unlike Exploratory Factor Analysis, CFA involves testing pre-established hypotheses regarding the relationships between observed and latent variables. Furthermore, CFA serves as a suitable analytical tool for scale development, validation, and the assessment of construct validity, as well as for evaluating factor invariance across different groups and time periods (Brown, 2006).

Confirmatory factor analysis (CFA), also known as structural equation modeling, plays a crucial role in validating models and conducting path analyses. Since the late 1990s, it has garnered significant attention in various applications within the field of measurement development, particularly in education and psychology (Russell, 2002).

Steps of Factor Analysis

1. Procedural Steps of Exploratory Factor Analysis (EFA):

The procedural steps for exploratory factor analysis are as follows (Saleh, Ahmed, 2023):

Defining the Objective of Exploratory Factor Analysis: Costello and Osborne (2005)

Exploratory factor analysis requires careful decisions regarding extraction methods, factor retention, and rotation techniques to produce meaningful results (Costello & Osborne, 2005). It is commonly

employed during the initial stages of instrument development to uncover latent dimensions among measured variables (Yong & Pearce, 2013).

Factor analytic evidence is one of the strongest sources of support for the construct validity of psychological and educational measures (Thompson & Daniel, 1996) and the best practices in exploratory factor analysis emphasize careful selection of extraction methods, rotation procedures, and criteria for factor retention (Watkins, 2018).

The objective of using this factor is to explore the internal structure of a set of items or variables.

- **Assessing data suitability for Exploratory Factor Analysis (EFA):** Before conducting the analysis, the suitability and adequacy of the sample size must be verified using the Kaiser-Meyer-Olkin (KMO) test:

- o Value $\geq 0.80 \rightarrow$ Excellent
- o Between 0.70 and 0.79 $\rightarrow$ Good
- o Between 0.60 and 0.69 $\rightarrow$ Acceptable
- o Less than 0.50 $\rightarrow$ Unsuitable for factor analysis.

Additionally, the presence of significant correlations between variables must be verified using Bartlett's Test of Sphericity: the result must be statistically significant (Sig < 0.05) to indicate that factor analysis is appropriate.

- **Selecting the Extraction Method:** The goal of extraction is to determine the number of initial factors. Common methods include:

Principal Component Analysis (PCA): The most frequently used starting point.

Principal Axis Factoring (PAF): Used when it is assumed that there are true latent factors underlying the variables.

- **Determining the Number of Factors (Factor Retention):** The number of factors to be retained is determined using:

•**Eigenvalue (> 1):** Retaining factors with an eigenvalue greater than 1.

•**Scree Plot:** Identifying the point where the curve begins to level off (the "elbow" point).

•**Cumulative Variance Explained:** Ideally, the selected factors should explain at least 50–60% of the total variance.

- **Factor Rotation:** The purpose of rotation is to simplify the interpretation of factors and ensure that items clearly belong to a single factor. Types of rotation include:

* **Orthogonal Rotation:** Such as Varimax—assumes that factors are uncorrelated.

•**Oblique Rotation:** Such as Oblimin or Promax—allows for correlation between factors.

- **Factor Interpretation:** Factor loadings for each item are examined to determine which factor it belongs to. An item is typically considered associated with a factor if its loading is at least 0.40 or 0.50. Items with low loadings or those that are cross-loading (sharing high loadings across more than one factor) are excluded or revised.

- **Naming Factors:** Once the items belonging to each factor are identified, their linguistic and conceptual content is analyzed to assign a descriptive name that reflects the factor's psychological or educational significance.

2. Procedural steps for using Confirmatory Factor Analysis (CFA):

When employing Confirmatory Factor Analysis, the researcher must follow these steps (Boudali, 2024):

- Constructing a theoretical model for the study derived from existing theories or prior research.
- Pay attention to sample size; Amos requires a large sample—at least 384 individuals (based on Steven or Morgan’s statistical guidelines) or a size calculated as the number of questions multiplied by ten.
- Verify the absence of missing values in the dataset within SPSS.
- Check for outliers, as they affect the normal distribution required by Amos.
- Develop the study instruments—such as questionnaires, scales, or interviews—to measure the relationships between latent and observed variables, which form the basis of the model.
- Verifying the validity and reliability of the data after collection.
- Linking data from SPSS to Amos software.
- Verifying the model's validity and reliability using Exploratory Factor Analysis (EFA).
- Testing the goodness-of-fit between the theoretical model and the field study data.
- Constructing a visual model based on the study's analytical model and hypotheses.
- Analyzing, interpreting, and understanding Amos output results based on goodness-of-fit indices.
- Modifying the model structure based on the results if the initial model is invalid.

3. Goodness-of-fit indices:

Goodness-of-fit indices are represented by: (Al-Rabie & Abdel-Halim, 2022)

Testing Model Fit Quality via Fit Indices

"Fit" refers to the extent to which the model successfully utilizes all the information contained in the original data, or the degree to which the model represents the sample data without deviating significantly from it. Consequently, numerous indices have been proposed to assess fit. While various classification systems exist, the most widely used and common approach categorizes these diverse fit indices into three major groups:

- Group One

Absolute Fit Indices. These are termed "absolute" because they do not rely on comparing the fit of the hypothesized model against other, more restricted models.

- Group Two

Comparative or Incremental Fit Indices. These indices estimate the relative improvement in fit achieved by the hypothesized model (the researcher's model) compared to a baseline model. The baseline model is typically the model involving the independent variables—often referred to as the "Independent Model" or "Null Model"—which is based on the assumption that the covariances among the observed variables in the population are zero (or non-existent), leaving only the variances of these variables.

- Group Three

Parsimony Correction Indices (or parsimony indices). These indices differ from the Chi-square index, the Standardized Root Mean Square Residual (SRMR), and others by incorporating a "penalty

function" applied when free parameters are added to the model without a corresponding improvement in the fit of the hypothesized model. This scenario represents a lack of parsimony regarding the variables or unconstrained free parameters requiring estimation. An applied example illustrating the steps of factor analysis on the Digital Teaching Skills Scale developed by the researcher:

Exploratory Factor Analysis

Factor analysis is a fundamental procedure for identifying the underlying dimensions of personality constructs and improving the psychometric quality of measurement scales (Briggs & Cheek, 1986).

To conduct an exploratory factor analysis, it is first necessary to verify that the conditions for its application are met and to assess the suitability of the data for factor analysis. Consequently, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity were calculated; these are among the most important statistical tools for assessing the suitability of the correlation matrix for exploratory factor analysis. The following table presents these results:

Table (01): *Verification of the conditions for applying exploratory factor analysis.*

Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test		
0.923		Kaiser-Meyer-Olkin Measure of Sampling Adequacy
5287.95	Approx. Chi-Square	Bartlett's Test of Sphericity
630	Degrees of Freedom	
0.000	Significance	

Table (01) shows that the KMO index value is 0.923, which is very high. According to the criteria established by Kaiser (1974), values ranging from 0.90 to 1.00 are considered excellent; this indicates that the sample size and the quality of inter-variable correlation are highly sufficient for conducting factor analysis. Consequently, it can be stated that the variables under study share a significant amount of common variance, thereby reinforcing the suitability of applying factor analysis to them.

Regarding the results of Bartlett's test of sphericity, the approximate Chi-square value was 5,287.795 with 630 degrees of freedom, and the statistical significance level was 0.000 (i.e., less than 0.001). This result indicates the rejection of the null hypothesis—which posits that the correlation matrix is an identity matrix (implying the variables are uncorrelated)—thereby demonstrating that the variables exhibit statistically significant correlations sufficient to justify the application of factor analysis.

Based on the values obtained for the KMO index and Bartlett's test, it can be concluded that the data possess a high degree of homogeneity and internal intercorrelation, rendering them entirely valid and suitable for conducting exploratory factor analysis.

Exploratory factor analysis was applied to the (36) items of the Digital Education Skills Scale, resulting in the saturation of all (36) items across six (6) dimensions, as shown in Table (2) below. The following were used as a result of the exploratory factor analysis:

4- The scale was administered to a sample of 200 teachers.

5- Extraction method: Principal Component Analysis (PCA).

6- Rotation method: Varimax with Kaiser normalization, which accepts the concept of simple construction while maintaining orthogonality between factors. Most researchers in the field of

education tend to use Kaiser's Varimax method, which leads to the best solutions that meet the characteristics of simple construction. (Ahmed Abu Fayyad, 2016)

7- Number of dimensions extracted: 6 dimensions

8- Number of variables: 36 items

Table No. (02): Shows the exploratory factor analysis, the dimensions (skills), and the item number in each dimension

Dimensions	Items
First	15, 16, 18, 19, 26, 27, 28, 29, 30
Second	01, 02, 03, 04, 05, 06
Third	07, 08, 09, 10, 11, 12, 17
Fourth	13, 14, 20, 21, 22, 23, 24, 25
Fifth	31, 32, 33, 34
Sixth	35, 36

Table (02) shows that the digital teaching skills measurement tool consisted of six dimensions, with the items distributed among them as follows: the first dimension (or skill) comprised 9 items; the second skill, 6 items; the third skill, 7 items; the fourth skill, 8 items; the fifth skill, 4 items; and the sixth skill, 2 items. Each dimension—corresponding to a specific skill—is designated as shown in the following table:

Table (03): Exploratory Factor Analysis: Dimensions (Skills) and Item Factor Loadings (N=200)

Saturation Level	Items	Dimensions
0.55	I can manage digital forums to discuss course topics	Digital Interaction and Assessment Skills
0.67	I use the commenting feature within educational applications to foster digital dialogue.	
0.65	I use notifications within digital platforms to maintain continuous interaction with students.	
0.65	I use applications designed to monitor student interaction.	
0.69	I use digital learning platforms to create electronic assessments.	
0.73	I assess students using clear and specific digital criteria	
Dimension	Item	Factor Loading
Digital Interaction and Assessment Skills	I monitor students' performance using the platform's learning analytics tools.	0.82
	I use digital rubrics to clarify assessment criteria.	0.68

Dimension	Item	Factor Loading
	I provide continuous feedback to students through digital tools.	0.66
	I possess basic computer skills.	0.76
Technical Skills	I can use the university's Learning Management System (LMS) efficiently.	0.78
	I am proficient in using presentation software.	0.77
	I use a variety of digital applications to support the teaching process.	0.70
	I can manage a virtual classroom using technological applications.	0.63
	I can troubleshoot simple technical problems during online lectures.	0.58
	I can develop digital instructional content that aligns with the course objectives.	0.62
	I can design digital learning materials that accommodate students' individual differences.	0.63
	I can use digital tools to organize and manage students' projects.	0.63
	I plan interactive learning activities to be implemented in digital learning environments.	0.49
	I can use an interactive whiteboard to deliver lessons.	0.71
Digital Pedagogical Skills	I integrate multimedia into the presentation of digital instructional content.	0.59
	I can use interactive digital tools that enable students to ask questions and express their concerns.	0.54
Digital and Citizenship Skills	I can use the Moodle platform to publish course materials.	0.41
	I encourage students to interact through digital learning platforms.	0.58
	I respect intellectual property rights when using digital resources.	0.74

Dimension	Item	Factor Loading
	I handle students' personal data and information with care and confidentiality.	0.75
	I guide students toward responsible online behavior.	0.58
	I use strong passwords and regularly update my software for security purposes.	0.56
	I adhere to the university's policies regarding the use of technology in teaching.	0.53
	I publish course lectures in accordance with intellectual property regulations.	0.51
Digital Professional Development Skills	I participate in professional development programs related to digital education.	0.72
	I keep up with the latest digital education tools and apply them in my teaching.	0.55
	I develop innovative approaches to make digital lectures more engaging for students.	0.71
	I develop interactive digital learning content that enhances students' understanding.	0.59
Skills in Integrating Artificial Intelligence into Digital Education	I use artificial intelligence technologies to improve the quality of the teaching and learning process.	0.78
	I am proficient in using artificial intelligence tools to effectively develop instructional content.	0.74

Based on Table (03) and the statistical analysis of the items—specifically, exploratory factor analysis (EFA) with orthogonal rotation—it can be seen that the items initially belonging to the dimensions "Digital Interaction Skills" and "Digital Assessment Skills" have been combined into a single dimension entitled "Digital Interaction and Assessment Skills." This merged dimension constitutes the first factor, composed of nine items. It is followed by the second dimension, "Technical Skills," which has retained all six of its original items. Next come the third dimension, "Digital Educational and Pedagogical Skills" (seven items), the fourth dimension, "Digital Engagement Skills" (eight items), and finally the fifth dimension, "Digital Professional Development Skills" (four items).

Next is the new sixth dimension—titled "Skills for Employing Artificial Intelligence in Digital Education"—which consists of two items.

Thus, the digital education skills assessment tool comprises six dimensions containing a total of 36 items. It utilizes a five-point scale (ranging from 1 to 5), with a maximum total score of 180. The

following table summarizes the digital education skills assessment; note that upon actual administration, the scale expands to account for each individual item.

Table (4): Dimensions, number of items, and scoring for the digital education skills assessment tool.

Dimensions	Number of Items	Maximum Score
Digital Interaction and Assessment Skills	9	45
Technical Skills	6	30
Digital Pedagogical Skills	7	35
Digital Citizenship and Responsibility Skills	8	40
Digital Professional Development Skills	4	20
Skills in Using Artificial Intelligence for Digital Education	2	10

Consequently, exploratory factor analysis revealed that the scale had evolved into a second version comprising six dimensions—distinct from the initial version—while retaining all 36 original items.

These findings align with the results of Al-Mahya's 2019 study, as the exploratory factor analysis process successfully extracted the scale's dimensions in compliance with all requisite conditions. Thus, the hypothesis was confirmed: the scale possesses a factor structure consisting of six dimensions associated with the items comprising the Digital Teaching Skills Scale.

Upon completion of the Exploratory Factor Analysis (EFA) and verification of the data's suitability for factor analysis, the instrument's preliminary factor structure was established, identifying the latent factors (dimensions) and their associated items. Based on the EFA results, the process proceeds to Confirmatory Factor Analysis (CFA) to assess the fit of the proposed factor model against the actual data. This analysis aims to test the model's goodness-of-fit—evaluating statistical indicators such as overall fit indices—and to confirm the stability of the dimensions and the construct validity of the instrument.

9- Confirmatory Factor Analysis:

Confirmatory factor analysis is used to test whether observed data fit a hypothesized measurement model based on theoretical expectations (Brown, 2015). Based on the results of the exploratory factor analysis and the output from the AMOS software, the results of the confirmatory factor analysis are as follows:

10- Confirmatory Factor Analysis Model: The theoretical model for the scale's content was defined according to a first-order, multidimensional confirmatory factor analysis model; Table (05) illustrates this:

Skill Category	Associated Variables
Digital Interaction and Assessment Skills	VAR00015, VAR00016, VAR00018, VAR00019, VAR00026, VAR00027, VAR00028, VAR00029, VAR00030

Technical Skills	VAR00001, VAR00002, VAR00003, VAR00004, VAR00005, VAR00006
Digital Pedagogical Skills	VAR00007, VAR00008, VAR00009, VAR00010, VAR00011, VAR00012, VAR00017
Digital Commitment Skills	VAR00013, VAR00014, VAR00020, VAR00021, VAR00022, VAR00023, VAR00024, VAR00025
Digital Professional Development Skills	VAR00031, VAR00032, VAR00033, VAR00034
Artificial Intelligence Skills in Digital Education	VAR00035, VAR00036

Table (05): Illustrates the theoretical factor model for the Digital Education Skills Scale according to the AMOS program.

The multifactor confirmatory factor model is based on the following assumptions: First, the assumption of the existence of a number of underlying factors; second, the assumption that these underlying factors are interconnected (double-pointing arrows connect them), meaning that there is a common area of meaning among these three factors, such that this commonality of meaning indicates the existence of a specific concept reflecting this shared meaning among the factors; third, identifying each factor by proposing a name for it; and fourth, defining the indicators for each factor, as the factor is measured and its existence is inferred through these indicators. (Tighza, 2012)

11- Study Model: The model was tested using AMOS software, as shown in Table (06) below:

Table (06): Standardized Regression Weights of the Study Model

Latent Variable (Construct)	Observed Variable (Item)	Standardized Loading (β)
Digital Interaction and Assessment Skills	VAR00015	0.69
	VAR00016	0.79
	VAR00018	0.83
	VAR00019	0.77
	VAR00026	0.78
	VAR00027	0.86
	VAR00028	0.73
	VAR00029	0.78
	VAR00030	0.75
Technical Skills	VAR00001	0.62

	VAR00002	0.70
	VAR00003	0.69
	VAR00004	0.76
	VAR00005	0.84
	VAR00006	0.82
Digital Pedagogical Skills	VAR00007	0.72
	VAR00008	0.80
	VAR00009	0.89
	VAR00010	0.84
	VAR00011	0.62
	VAR00012	0.82
	VAR00017	0.82
Digital Commitment Skills	VAR00013	0.52
	VAR00014	0.65
	VAR00020	0.59
	VAR00021	0.57
	VAR00022	0.47
	VAR00023	0.60
	VAR00024	0.67
	VAR00025	0.56
Digital Professional Development Skills	VAR00031	0.71
	VAR00032	0.85
	VAR00033	0.81
	VAR00034	0.85
Artificial Intelligence Skills in Digital Education	VAR00035	0.85
	VAR00036	0.98

Table (06): Illustrates the applied factor model for the digital teaching skills scale using the AMOS program.

Figure (06) shows that the model consists of 36 items distributed across six dimensions, in the following order: digital interaction and assessment skills; technical skills; digital educational and pedagogical skills; digital commitment skills; digital professional development skills; and skills for utilizing artificial intelligence in digital education. Each dimension comprises a set of items, with each item linked to its own specific measurement error. The values associated with the arrows connecting the dimensions (skills) and the items indicate that most items are strongly correlated with the dimensions they measure (mostly exceeding 0.60), signifying high quality in how well the items represent the dimensions (skills).

Regarding the interrelationships among the six dimensions, correlation coefficients ranged from 0.36 to 0.83. Notably strong correlations were observed between the "digital interaction and assessment skills" dimension and the "digital pedagogical skills" dimension ($r = 0.83$); between the "technical skills" dimension and the "digital pedagogical skills" dimension ($r = 0.83$); between the "digital interaction and assessment skills" dimension and the "AI utilization skills" dimension ($r = 0.81$); and between the "digital professional development skills" dimension and the "digital pedagogical skills" dimension ($r = 0.78$).

Meanwhile, a moderate correlation was found between the "digital interaction and assessment skills" dimension and the "technical skills" dimension ($r = 0.65$) and between the digital professional development dimension and the technical skills dimension with a correlation coefficient of 0.65; between the professional development skills dimension and the digital commitment dimension with a correlation coefficient of 0.63; between the AI utilization skills dimension and the digital educational and pedagogical skills dimension with a correlation coefficient of 0.61; between the digital professional development skills dimension and the AI utilization skills dimension with a correlation coefficient of 0.59; between the digital professional development dimension and the digital interaction and assessment skills dimension with a correlation coefficient of 0.51; and between the digital commitment skills dimension and the technical skills dimension with a correlation coefficient of 0.48.

In contrast, a weak correlation (0.36) was observed between the dimension of AI application skills and the dimension of digital commitment skills.

It can be concluded that the model demonstrates a coherent, multidimensional factor structure for measuring digital education skills, featuring strong factor loadings on their respective dimensions—thereby supporting the validity of the scale's items—while the inter-dimensional correlations indicate generally positive relationships among the skills within the digital education skills scale.

12- Goodness-of-Fit Model:

Goodness-of-fit indices assess the degree of proximity between the correlation matrix input into the software and the matrix derived from it following Confirmatory Factor Analysis (CFA). This involves comparing the hypothesized model against two benchmarks: the "independence model" (representing the poorest fit) and the "saturated model" (representing the best fit). Ultimately, the assessment of fit aims to determine the extent to which the model effectively utilizes the information contained in the data and the degree to which the hypothesized model can reproduce the original model's covariance matrix. (Abdul-Nasser, 2018)

Goodness-of-fit indices aim to compare the sample covariance matrix with the covariance matrix derived from the results of confirmatory analysis. This process involves estimating the discrepancy

between the two matrices—referred to as the "fit function" (denoted by $*F*$)—which is a positive function reflecting the distance between the matrices. Examples of such indices include:

- Chi-Square (χ^2) index
- Normalized Chi-Square index
- Root Mean Square Residual (RMR) index
- Standardized Root Mean Square Residual index
- Root Mean Square Error of Approximation (RMSEA)
- Goodness of Fit Index (GFI)

The second category consists of comparative or incremental fit indices. These are based on comparing the calculated chi-square value of the research's theoretical model with that of a baseline model—specifically the "independent" or "null" model. In the context of Confirmatory Factor Analysis (CFA), the null model assumes no relationship between the latent variables (factors) and the observed items. Consequently, the comparison is made between the hypothesized model and this null (or independent) model—which represents a poor fit. Thus, these indices aim to assess the extent to which the hypothesized model improves upon the poorly fitting independent model. This category includes several indices, such as:

Normed Fit Index (NFI)

-Non-Normed Fit Index (NNFI)

-Comparative Fit Index (CFI)

These indices aim to determine the ratio between the chi-square value of the proposed model and that of the independent model. Their values range from 0 to 1, with an optimal value of 0.90 or higher indicating a good fit (Ibrahim, 2020). According to Tighza (2012), goodness-of-fit indices provide the researcher with the standard error values for the parameters. These indices were obtained using the AMOS software, and the results were as follows:

Table 7. Goodness-of-Fit Indices for the Measurement Model

Fit Index	Acceptance Criteria	Observed Value	Interpretation of Model Fit
Absolute Fit Indices			
Chi-square (χ^2) or CMIN	Should be statistically non-significant	$\chi^2 = 1377.628$ df = 579	The index is not accepted because the Chi-square value is statistically significant. However, the Chi-square statistic is highly sensitive to sample size and is rarely non-significant; therefore, the remaining fit indices are considered for model evaluation.
Normed Chi-square (NC = χ^2/df)	Acceptable values range from 1 to 5. A value ≤ 3 indicates an acceptable	2.379	The χ^2/df ratio is 2.379 , which is below 3, indicating that the model adequately fits the data.

Fit Index	Acceptance Criteria	Observed Value	Interpretation of Model Fit
	fit, while ≤ 2 indicates a very good fit.		
Root Mean Square Residual (RMR)	Lower values indicate better fit; a value of zero represents perfect fit.	0.087	Since the value is relatively close to zero, the model demonstrates acceptable fit.
Root Mean Square Error of Approximation (RMSEA)	Acceptable values range from 0.05 to 0.10.	0.083	The value falls within the acceptable range, indicating adequate model fit.
Goodness-of-Fit Index (GFI)	Should be equal to or greater than 0.90.	0.727	The criterion for acceptable fit was not met.
Comparative / Incremental Fit Indices			
Comparative Fit Index (CFI)	Values range between 0 and 1; values closer to 1 indicate better fit.	0.841	The value falls within the acceptable range and indicates satisfactory model fit.
Tucker–Lewis Index (TLI) / Non-Normed Fit Index (NNFI)	Should be greater than 0.90.	0.827	The value is close to the recommended threshold but does not achieve acceptable model fit.
Normed Fit Index (NFI)	Should be greater than 0.90.	0.756	The criterion for acceptable fit was not met.
Parsimony Fit Indices			
Expected Cross-Validation Index (ECVI)	A lower value than that of the proposed (independence) model indicates better fit.	7.797	The model demonstrates acceptable fit because the obtained value is lower than that of the hypothesized (comparison) model.
Consistent Akaike Information Criterion (CAIC)	The current model should have a lower value than the independence model.	1925.582	The model demonstrates acceptable fit because the obtained value is lower than that of the comparison (independence) mode

Table (07) shows that the goodness-of-fit indices indicate an acceptable-to-good fit between the proposed model and the study data. While the absolute fit indices revealed a statistically significant Chi-square (χ^2) value ($p < 0.05$)—a result likely attributable to the test's sensitivity to large sample sizes, making it unsuitable as a sole criterion for assessing model quality—the normalized Chi-square value (CMIN/DF or NC) was below 3. This indicates that the model achieves a good level of fit according to established statistical standards.

The model achieved acceptable fit regarding the Root Mean Square Error of Approximation (RMSEA), as well as the Comparative Fit Index (CFI) and Root Mean Square Residual (RMR)—with values falling within the corresponding standard ranges—thereby supporting the model's fit to the data. Regarding the Expected Cross-Validation Index (ECVI) and the Consistent Akaike Information Criterion (CAIC), the model yielded lower values than the independent model, reinforcing the efficiency of the proposed model compared to alternatives. However, values for the Tucker-Lewis Index (TLI), Goodness of Fit Index (GFI), and Normed Fit Index (NFI) fell below the recommended threshold (0.90), indicating that the model's fit according to these specific indices did not meet the desired standard, despite achieving acceptable fit on the other indices.

Confirmatory factor analysis results indicate that the proposed model achieves an acceptable level of fit with the data; key fit indices—such as CMIN/DF, RMSEA, CFI, CAIC, ECVI, and RMR—fell within statistically acceptable limits. Consequently, the instrument demonstrates good construct validity, as its items appropriately reflect the intended theoretical dimensions. Although some secondary fit indices (GFI, NFI, and TLI) did not reach ideal values, this does not undermine the validity of the structural model, as their values were very close to the required rank. Tabachnick and Fidell (2019). Researchers should verify assumptions such as sampling adequacy and sufficient intercorrelations among variables before conducting factor analysis (Tabachnick & Fidell, 2019).

Validity is a unified concept that integrates evidence regarding the meaning and interpretation of test scores as well as their intended uses (Messick, 1995). Thus, the construct validity underpinning the digital teaching skills scale is confirmed.

Conclusion

It is evident from the foregoing that factor analysis is one of the most important multivariate statistical methods contributing to the advancement of psychological and educational measurement, as it provides robust scientific evidence for verifying the construct validity of scales and tests. Exploratory factor analysis enables the identification of a scale's underlying dimensions and the organization of its items into factors that reflect the theoretical construct being measured; meanwhile, confirmatory factor analysis allows for testing the fit of the theoretical model against empirical data, thereby enhancing measurement accuracy and the reliability of results.

The theoretical review also demonstrated that the successful application of factor analysis depends on adhering to a set of methodological steps and procedures—ranging from verifying data suitability and selecting the appropriate factor extraction method to determining the number of factors, performing rotation, and finally interpreting the factors and evaluating model quality using statistical fit indices. These procedures provide a scientific foundation for developing measurement tools characterized by high levels of validity and reliability, thereby positively influencing the quality of psychological and educational studies and the validity of their conclusions.

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