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Item Rotation in Scale Development: Exploring Principles and Strategies for Improving Scale Validity and Interoperability through Factor Analysis

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Abstract
Item rotation plays a crucial role in factor analysis during the development of measurement scales, aiming to enhance scale validity and interoperability. This paper investigates the theoretical foundations of item rotation and examines the underlying principles and strategies that contribute to the improvement of scale validity and interoperability. The study explores the role of factor analysis as a statistical tool for extracting latent factors and investigates how different item rotation methods can optimize the interpretability and reliability of measurement scales. Additionally, the paper discusses the theoretical considerations guiding the selection of appropriate item rotation techniques, such as orthogonal and oblique rotations, and their implications for scale development and measurement theory. By synthesizing existing literature and providing practical insights, this study aims to contribute to a comprehensive understanding of item rotation and its theoretical significance in the process of scale development.
Keywords: ***Item rotation, measurement scales, reliability, scale development, validity.***

Introduction

The construction of trustworthy and accurate measuring scales is crucial in the field of social sciences. Measurement scales allow for the systematic exploration and analysis of a variety of categories, including attitudes, beliefs, and behaviours (Alordiah & Ossai, 2023). Factor analysis has become a frequently used statistical approach to assess the reliability and correctness of these scales. (Akhtar-Danesh, 2017). In the social sciences and education, measurement scales are essential instruments for encoding and measuring abstract notions. They offer a way to gauge variables that are frequently elusive, arbitrary, or complicated. (Schreiber, 2021). Researchers may evaluate data, come to meaningful findings, and make well-informed judgments based on empirical evidence by operationalizing concepts into quantifiable indicators. For the advancement of scientific understanding, making comparisons between research easier, and guiding policy and practice, accurate measuring scales are crucial. (Kowarsch et el., 2016). A typical statistical technique used in scale construction is factor analysis, which identifies the underlying latent dimensions or factors that account for the observed variance in a collection of variables. Factor analysis assists researchers in reducing the dimensionality of data, detecting correlations between items, and comprehending the underlying structures by discovering the latent structure (Ardura et al., 2018; Alordiah, 2015). By combining related elements into coherent components, this technique permits the development of brief and understandable measuring scales. Item rotation, a crucial stage in the factor analysis method, is used to improve the interpretability and validity of the produced factors. The goal of item rotation is to reorient the factor structure so that each item primarily loads on one component, resulting in simple, understandable patterns that make interpretation easier. The rotation procedure, which is supported by theoretical concepts, tries to maximize factor loadings and minimize cross-loadings in order to maximize the interpretability of the factors. Proper item rotation is essential to improve construct validity, the measuring scale, and the meaning and dependability of the results (Schmitt et el., 2011).

To improve scale validity and interoperability through factor analysis, this study will examine the theoretical underpinnings of item rotation in scale construction. It will also investigate the guidelines and strategies used in this process. The following are the precise goals:

- To investigate the theoretical foundations of factor analysis' item rotation.
- To investigate the various rotation techniques, such as oblique and orthogonal rotations, and their effects on scale growth.
- To investigate how item rotation enhances factor structure interpretability and hence scale validity.
- Examine how item rotation improves scale interoperability between various people, cultures, or circumstances.
- To list the difficulties and restrictions related to item rotation and suggest new lines of investigation.

Theoretical Foundations of Item Rotation

In the social sciences and education, the systematic process of developing and testing measuring scales to evaluate and quantify abstract attributes is referred to as scale development (Pelletier et el., 2023). In order to enable researchers to gather and examine data pertaining to these attributes, it is important to operationalize theoretical notions into observable and quantifiable indicators. Scale development is a difficult endeavour with many obstacles. Concept underrepresentation, which happens when the scale does not capture all the pertinent components of the theoretical construct, is a problem (Smith et el., 2021). Concept-irrelevant variance occurs when the scale contains items that assess aspects unrelated to the target construct, is another difficulty. Additionally, problems including response bias, ambiguous items, and poor scale reliability and validity may be encountered by researchers (Hastie et el., 2023) These difficulties may result in erroneous measurement and impede the appropriate interpretation of study results. The importance of item rotation in overcoming the difficulties in scale development cannot be overstated (Cordova et el., 2017) Item rotation is a technique used in factor analysis to reorient the components to produce patterns that are straightforward and easy to comprehend.

Principles of Factor Analysis

The contrast between latent variables and observable variables is the foundation of factor analysis. Latent variables, often called factors, are unobservable entities that have an impact on the variables that can be seen. They stand for the fundamental qualities or characteristics that underlie the relationships between the measured variables (Alavi et el., 2020; Alordiah, 2015; Alordiah & Agbajor, 2014). The evident indicators that are directly measured or observed in a study are known as observed variables. To comprehend the construct's structure, factor analysis seeks to locate and separate these latent variables from the observable variables (Alordiah, 2022; Alavi et el., 2020).

Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) are the two basic methods used in factor analysis. When the underlying factor structure is not well-established or when the researcher wants to investigate and locate the latent variables in the data, EFA is an exploratory approach that is utilized. It enables an objective investigation of the factor structure. Contrarily, CFA is a confirmatory approach that evaluates a proposed factor structure in light of a priori theory or previously known information (Nájera et el., 2023). CFA is used when researchers have specific hypotheses about the factor structure and aim to confirm or validate the structure through statistical analysis.

A number of presumptions form the foundation of factor analysis, including the linearity presumption, which holds that interactions between variables are linear. The assumption of common factors, which contends that the observable variables share variance because of shared latent components, is another supposition. Furthermore, component analysis makes the assumption that there are enough observations relative to the number of variables being studied. The validity and reliability of the results of the factor analysis may be impacted if certain assumptions are broken. Additionally, factor analysis has drawbacks such the reliance on subjective judgments throughout the study and the difficulty to demonstrate causation. (e.g., selection of rotation method), and sensitivity to sample size and characteristics (Alavi et el., 2020).

Exploratory Factor Analysis (EFA)

When researchers want to investigate and discover the underlying component structure inside a collection of observable data, they use exploratory factor analysis (EFA). Finding the latent variables or factors that contribute to the observed variation in the data is the main goal of EFA. EFA permits a dispassionate analysis of the data without making assumptions about the factor structure. It enables researchers to understand the correlations between the variables that were observed and to locate the underlying dimensions or constructs (Roberson et el., 2014).

There are various steps in the EFA procedure. The researcher first chooses on a collection of observed variables, the best statistical approach to apply, and the rotation method. The researcher next looks at the communalities, which show how much of each observed variable's variation can be accounted for by the components that were extracted. The elements are then extracted using techniques like principal component analysis or maximum likelihood estimation. To create a factor structure that is simpler and easier to understand, item rotation is done last (Koyuncu et el., 2019). The extraction of latent components is a crucial step in EFA. To estimate the components based on the interactions between the observable variables, extraction techniques like principal component analysis or common factor analysis are utilized. These techniques seek to pinpoint the variables that contribute the most variation to the observed variables. The underlying dimensions that account for the correlations between the observed variables are represented by the extracted factors (Oamen, 2021). An initial factor solution is obtained after factor extraction. The pattern of factor loadings for each observed variable is represented by the first factor solution, which also shows the direction and intensity of the link between the observed variable and the extracted factors. The number of significant factors to keep is determined by looking at eigenvalues, which show how much variance each component explains. The number of elements to keep in the final solution can be determined using eigenvalues higher than 1 or a scree plot (Gaskin et el., 2014).

Confirmatory Factor Analysis (CFA)

When researchers have a pre-established theoretical framework or precise assumptions about the underlying factor structure, they use confirmatory factor analysis (CFA). CFA uses statistical analysis to verify or validate the proposed factor structure. CFA measures the goodness-of-fit between the actual data and the theoretical expectations by determining how well the observed data match the proposed model (Koyuncu et el., 2019).

Model may be made, such as allowing for correlated errors or removing items with low factor loadings. The process of CFA involves several steps. Researchers start by specifying the hypothesized factor structure based on prior theoretical knowledge or existing literature. The model is then estimated using various estimation methods, such as maximum likelihood estimation. Fit indices are calculated to assess how well the observed data align with the hypothesized model. If the fit indices indicate a poor fit, modifications to the CFA tests the hypothesized factor structure by evaluating the fit between the observed data and the theoretical model (Ayob et el., 2017). The model specifies the relationships between the observed variables and the latent factors, including the factor loadings and the covariances or correlations among the factors. CFA examines whether the observed data align well with the expected pattern of relationships based on the hypothesized model(Kyriazos et el., 2019).

Fit indices are utilized to assess the goodness-of-fit between the observed data and the hypothesized model in CFA. These indices provide quantitative measures of how well the data fit the model. Common fit indices include the chi-square test, comparative fit index (CFI), Tucker-Lewis Index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Researchers interpret these fit indices to determine if the observed data adequately match the hypothesized model. A good fit indicates that the hypothesized model accurately represents the relationships among the variables (Carle et el., 2015).

Latent Variable Extraction and Rotation

In factor analysis, the extraction of latent variables, also known as factors, is a fundamental step. Latent variable extraction involves identifying and estimating the underlying dimensions that explain the relationships among the observed variables (Hojat et el., 2014). The extraction process aims to determine the most accurate representation of the latent variables within the data.

There are various extraction methods used in factor analysis, including principal component analysis (PCA), confirmatory factor analysis (CFA), and maximum likelihood estimation (MLE). These methods differ in their underlying assumptions and estimation techniques. PCA aims to extract factors that account for the maximum variance in the observed variables, while CFA seeks to extract factors that represent the shared variance among the observed variables (Alavi et el., 2020). MLE estimates the factors based on the maximum likelihood of the observed data given the hypothesized factor structure. The extraction methods provide estimates of factor loadings, which indicate the strength and direction of the relationship between the observed variables and the extracted factors. These factor loadings represent the weights assigned to each observed variable in contributing to the latent factor.

Types of Rotation Methods

After the extraction of latent variables, item rotation is applied to enhance the interpretability of the factor structure. Item rotation aims to achieve a simpler and clearer pattern of factor loadings, making it easier to interpret the meaning of the factors. There are different types of rotation methods used in factor analysis, including orthogonal rotation, oblique rotation, and hybrid rotation (Nguyen et el., 2022).

Orthogonal Rotation: Orthogonal rotation methods assume that the factors extracted are independent of each other. In orthogonal rotation, the factor axes are perpendicular to each other, meaning that the factors are uncorrelated. Orthogonal rotation simplifies the factor structure by forcing each observed variable to load predominantly on one factor, minimizing cross-loadings. Varimax, Quartimax, and Equamax are common orthogonal rotation methods. Varimax rotation maximizes the variance of the factor loadings within each column, Quartimax rotation minimizes the number of factors needed to explain each variable, and Equamax rotation combines the characteristics of Varimax and Quartimax rotations (Visinescu et el., 2014).

Oblique Rotation: Oblique rotation methods relax the assumption of factor independence and allow for correlation between factors. Unlike orthogonal rotation, oblique rotation acknowledges that factors may be related and can have correlated variances. Oblique rotation facilitates a more realistic representation of the underlying structure when the factors are conceptually related. Promax and Direct Oblimin are popular oblique rotation methods. Promax rotation simplifies the factor structure by promoting simple structure and grouping related variables onto the same factor, while Direct Oblimin rotation allows for correlated factors and takes into account the shared variance among the factors (Lorenzo-Seva et el., 2009).

Hybrid Rotation: Hybrid rotation methods combine both orthogonal and oblique rotation techniques. These methods aim to strike a balance between the simplicity of orthogonal rotation and the flexibility of oblique rotation. Hybrid rotation allows for moderate inter-factor correlations while maintaining a relatively simple factor structure (Nguyen et el., 2022).

Theoretical Considerations in Item Rotation

Factor Structure Interpretation: Factor structure interpretation involves making sense of the patterns of factor loadings after item rotation. Researchers examine the factor loadings to understand the relationships between the observed variables and the latent factors. Higher factor loadings indicate a stronger association between an observed variable and a specific factor. Researchers consider the substantive meaning of the observed variables and their corresponding factors to interpret the underlying constructs.

Factor Variance Explained: Factor variance explained refers to the proportion of variance in the observed variables accounted for by the latent factors. It provides information about the importance and strength of the factors in explaining the variability in the observed variables. Researchers evaluate the factor variance explained to determine the relative contribution of each factor to the overall structure of the measurement scale (Kang, 2013).

Factor Loadings and Cross-Loadings: Factor loadings represent the strength and direction of the relationship between an observed variable and a latent factor. Higher factor loadings indicate a stronger association between the observed variable and the factor. Cross-loadings occur when an observed variable has substantial loadings on multiple factors. Minimizing cross-loadings is important to achieve a simple and interpretable factor structure (Nguyen et el., 2022).

Simple Structure and Factor Interpretability: Simple structure refers to a factor structure in which each observed variable loads significantly on only one factor and has minimal or no cross-loadings on other factors. Simple structure enhances the interpretability of the factors and facilitates a clearer understanding of the relationships between the observed variables and the latent factors. Researchers aim to achieve simple structure to ensure that the factors represent distinct and meaningful constructs (Scharf., 2019).

Strategies for Enhancing Scale Validity and Interoperability

Orthogonal Rotation Methods

Orthogonal rotation methods are widely employed in factor analysis to enhance the interpretability and validity of measurement scales. These methods assume that the extracted factors are independent of each other, meaning they are uncorrelated. Orthogonal rotation simplifies the factor structure by minimizing cross-loadings and promoting simple structure (Ricolfi et el., 2021).

Varimax Rotation

Varimax rotation is one of the most commonly used orthogonal rotation methods. It aims to maximize the variance of the factor loadings within each column, which leads to clearer and simpler factor structures. Varimax rotation achieves this by adjusting the factor loadings to minimize the number of variables with high loadings on each factor, while maximizing the number of variables with low or near-zero loadings (Weide et el., 2019). The procedure involves an iterative process of rotating the factors, re-estimating the factor loadings, and maximizing the variance until convergence is achieved. Varimax rotation offers several advantages. It simplifies the factor structure by producing factor loadings with high magnitudes on one factor and low magnitudes on others, resulting in more distinct and interpretable factors. Varimax rotation is particularly useful when the goal is to achieve factor independence and enhance the interpretability of the scale. However, Varimax rotation may not be suitable when factors are conceptually related or when cross-loadings are expected. Additionally, Varimax rotation assumes that each factor accounts for a significant amount of variance in the observed variables, which may not always hold true (Zhang et el., 2015).

Quartimax Rotation

Quartimax rotation is another orthogonal rotation method that simplifies the factor structure by minimizing the number of factors required to explain each variable. Quartimax rotation seeks to maximize the variance of each variable accounted for by the factors, rather than maximizing the variance within each factor. This results in factors that account for a larger proportion of the variance in each variable, leading to fewer factors overall. The procedure involves iteratively adjusting the factor loadings to achieve a simpler structure with fewer factors. Quartimax rotation offers advantages in terms of achieving parsimony and simplicity in the factor structure. By minimizing the number of factors needed to explain each variable, Quartimax rotation facilitates a more concise representation of the underlying constructs. This can be particularly useful when researchers aim to reduce the complexity of the measurement scale. However, Quartimax rotation may oversimplify the factor structure, potentially obscuring meaningful relationships among variables. It may also result in lower factor loadings, as the emphasis is on reducing the number of factors rather than maximizing the variance accounted for by each factor (Visinescu et el., 2014).

Equamax Rotation

Equamax rotation is an orthogonal rotation method that combines the characteristics of Varimax and Quartimax rotations. It seeks to strike a balance between maximizing the variance of the factor loadings within each factor (Varimax) and minimizing the number of factors needed to explain each variable (Quartimax). Equamax rotation allows for both factor independence and parsimony in the factor structure (Visinescu et el., 2014). The procedure involves iteratively adjusting the factor loadings to achieve an equilibrium between maximizing the variance and minimizing the number of factors. Equamax rotation provides a compromise between Varimax and Quartimax rotations, offering advantages in terms of interpretability and simplicity. By combining the goals of factor independence and parsimony, Equamax rotation can produce factors that are both distinct and concise. This can facilitate a more straightforward interpretation of the measurement scale. However, Equamax rotation may not be as effective as specialized methods like Varimax or Quartimax when it comes to maximizing the variance or minimizing the number of factors, respectively.

Other Orthogonal Rotation Methods

In addition to Varimax, Quartimax, and Equamax rotations, there are other orthogonal rotation methods that researchers can employ. These include Direct Oblimin, Geomin, and Orthomax rotations, among others. Each method has its own specific algorithm and criteria for achieving the rotation of factors. Researchers can explore these methods based on the specific needs of their study, the characteristics of their data, and the goals of the factor analysis (Nguyen et el., 2022).

Oblique Rotation Methods

Oblique rotation methods are alternative approaches to item rotation in factor analysis that relax the assumption of factor independence.Unlike orthogonal rotation methods, oblique rotation allows for the correlation between factors, recognizing that factors can be related or correlated. Oblique rotation methods provide more flexibility in representing the relationships among variables and can be particularly useful when factors are conceptually related(Lorenzo-Seva et el., 2009).

Direct Oblimin Rotation

Direct Oblimin rotation is a commonly used oblique rotation method that allows for correlated factors. It seeks to achieve a simpler factor structure by promoting a clearer distinction between factors while allowing for some correlation among them. The procedure involves iteratively adjusting the factor loadings and the correlations between factors to obtain a more interpretable factor structure (de Castro et el., 2015). The direct oblique rotation estimates the factor loadings and the inter-factor correlations simultaneously, resulting in a factor structure that accounts for both the shared and unique variance among the observed variables. Direct Oblimin rotation offers advantages in terms of representing the relationships among factors more accurately. By allowing for correlated factors, it acknowledges the potential interdependencies and captures the shared variance among the factors. This can be particularly beneficial when the factors are conceptually related or when there is a theoretical basis to expect correlations among factors. However, one limitation of Direct Oblimin rotation is that the interpretation of the inter-factor correlations can be more complex, as it introduces an additional aspect beyond the factor loadings. Additionally, the estimation of inter-factor correlations may require larger sample sizes compared to orthogonal rotation methods (Nguyen & Waller, 2022).

Promax Rotation

Promax rotation is another widely used oblique rotation method. It aims to simplify the factor structure by promoting simple structure and grouping related variables onto the same factor. Promax rotation estimates the factor loadings and then adjusts the inter-factor correlations to achieve a simpler and more interpretable factor structure. The procedure involves an iterative process of estimating the factor loadings, adjusting the inter-factor correlations, and repeating this process until convergence is reached (Grieder et el., 2022). Promax rotation provides flexibility in representing the relationships between factors while emphasizing the simplicity of the factor structure. Promax rotation offers several advantages. It allows for the representation of complex relationships among factors, facilitating the interpretation of the underlying constructs. Promax rotation can accommodate both correlated and uncorrelated factors, making it suitable for a wide range of research contexts. It promotes a simple structure by grouping related variables onto the same factor, enhancing the interpretability of the measurement scale (Nunes et el., 2020). However, one limitation of Promax rotation is that it may not provide as clear a distinction between factors as orthogonal rotation methods. The inter-factor correlations can complicate the interpretation of the factor structure, requiring careful consideration and analysis (Grieder et el., 2022).

Other Oblique Rotation Methods

In addition to Direct Oblimin and Promax rotations, there are other oblique rotation methods available for researchers to consider. These methods include Oblimin, Orthoblique, and Promin rotations, among others. Each oblique rotation method employs a distinct algorithm and set of criteria for adjusting the factor loadings and inter-factor correlations. Researchers can explore these methods based on the specific characteristics of their data, the nature of the relationships among factors, and the goals of the factor analysis (de Castro et el., 2015).

Comparing Orthogonal and Oblique Rotation

Differentiating Orthogonal and Oblique Rotation: Orthogonal and oblique rotations differ in their treatment of the factor intercorrelations. Orthogonal rotation methods assume that the factors are independent and uncorrelated, resulting in a factor structure with orthogonal axes. These methods aim to achieve a simple and clear factor structure by minimizing cross-loadings. On the other hand, oblique rotation methods allow for the correlation between factors, recognizing that factors may be related or correlated. Oblique rotation provides more flexibility in representing the relationships among variables and can capture the shared variance among factors (Nguyen & Waller, 2022).

When choosing between orthogonal and oblique rotation methods, researchers need to consider several factors. The decision depends on the nature of the research question, the theoretical framework, and the conceptual relationships among the factors. If factors are expected to be independent or uncorrelated, orthogonal rotation methods like Varimax or Quartimax may be appropriate. On the other hand, if factors are conceptually related or expected to be correlated, oblique rotation methods like Direct Oblimin or Promax may be more suitable. Researchers should select the rotation method that aligns with their research goals and theoretical assumptions (Bountziouka et el., 2021).

The choice between orthogonal and oblique rotation methods can have implications for scale validity and interoperability. Orthogonal rotation methods aim to achieve simple structure and minimize cross-loadings, which can enhance the clarity and interpretability of the factors. This may improve scale validity by ensuring that each observed variable predominantly loads on one factor. Oblique rotation methods allow for the representation of complex relationships among factors and capture the shared variance. While this flexibility can better reflect the underlying constructs, it may introduce additional complexity and require careful interpretation. The choice of rotation method should align with the goals of scale development and the specific requirements of the research context to ensure both validity and interoperability (de Castro et el., 2015).

Cross-Loadings and Residual Correlations

Cross-loadings and residual correlations are two important aspects to consider when examining the factor structure in item rotation during factor analysis. They provide valuable insights into the relationships among observed variables and the underlying latent factors (Christensen et al., 2020).

Cross-loadings refer to situations where an observed variable demonstrates substantial loadings on multiple factors. In other words, the observed variable shows a significant association with more than one latent factor. Cross-loadings can occur due to various reasons, such as shared variance among the factors or measurement error (Awwad et el, 2021). It is important to address cross-loadings because they can complicate the interpretation of the factor structure and potentially lead to ambiguous or misleading results. Minimizing cross-loadings is desirable to achieve a clear and meaningful factor structure.

Residual correlations, on the other hand, represent the correlations among the observed variables that are not accounted for by the extracted factors. These residual correlations can occur due to several reasons, including common method bias, omitted variables, or unique relationships among the observed variables. Residual correlations are important to consider as they provide insights into the presence of additional relationships among the observed variables beyond what is explained by the latent factors. Examining residual correlations can help identify potential measurement issues or sources of unexplained variance in the factor structure variables (Katicha et el., 2022).

Addressing cross-loadings and residual correlations requires careful examination and consideration. Several strategies can be employed to minimize cross-loadings, such as refining item wording, revising item content, or removing problematic items from the scale. It may also be necessary to explore the theoretical and conceptual relationships among the observed variables to identify potential sources of cross-loadings. Similarly, analysing residual correlations can provide insights into measurement artifacts or unaccounted relationships, which may require further investigation and adjustment in the factor analysis process (Scheer et al., 2018).

Interpreting Rotated Factor Structures

Interpreting rotated factor structures is a critical step in factor analysis as it allows researchers to make sense of the relationships between observed variables and the underlying latent factors. By examining factor loadings, pattern matrices, factor interpretation, and considering cross-loadings and residual correlations, researchers can gain insights into the meaning and validity of the factors. Factor loadings represent the strength and direction of the relationship between observed variables and the underlying latent factors. Higher factor loadings indicate a stronger association between an observed variable and a specific factor. Researchers often focus on the absolute magnitude of factor loadings, considering values above 0.30 or 0.40 as significant(Nguyen et el., 2022).

The pattern matrix displays the factor loadings for each observed variable. It provides a clear representation of which variables load heavily on which factors. By examining the pattern matrix, researchers can identify the variables that have the highest factor loadings and determine which factors they align with the most. This aids in interpreting the constructs represented by the factors(Alavi et el., 2020).

Factor interpretation involves assigning a meaningful interpretation or label to each factor based on the observed variables that load heavily on it. Researchers consider the content and context of the observed variables to determine the underlying construct that the factor represents. The interpretation should align with the theoretical framework or research question under investigation. Naming the factors is an important step in factor analysis. By providing a concise and descriptive name for each factor, researchers enhance the interpretability and communicability of the factor structure. The naming process involves considering the substantive meaning of the observed variables that load heavily on each factor and selecting a label that captures the essence of the construct represented by the factor (Jordan & Spiess, 2019).

Challenges and Limitations of Item Rotation

Item rotation in factor analysis is a valuable technique for enhancing scale validity and interpretability. However, it also presents some challenges and limitations that researchers need to be aware of and address appropriately. One challenge in item rotation is the possibility of over-extraction or over-factorization. Over-extraction occurs when too many factors are extracted, resulting in a complex and less interpretable factor structure. Over-extraction can lead to the inclusion of noise or irrelevant factors, reducing the clarity and validity of the measurement scale. To mitigate this challenge, researchers need to exercise caution and consider theoretical, empirical, and practical justifications for selecting the appropriate number of factors. Similarly, over-factorization can occur when the factor structure is overly complex and difficult to interpret. This can happen when researchers force more factors than necessary to improve the fit of the model or accommodate cross-loadings. Over-factorization can complicate the factor structure, making it challenging to identify clear and distinct constructs (Akhtar-Danesh, 2017). To address this challenge, researchers should prioritize simplicity and interpretability while determining the appropriate number of factors.

Item rotation may sometimes result in complex factor structures that are difficult to interpret or may lead to ambiguity in construct representation. This can occur when factors are highly correlated or when there are overlapping or similar items across factors. Complex factor structures can make it challenging to assign meaningful interpretations to the factors or to differentiate them from each other(Scharf et al., 2019). Researchers need to carefully consider the conceptual meaning of the factors and the content of the observed variables to minimize ambiguity and improve interpretability.

Moreover, ambiguity can arise when items exhibit substantial cross-loadings or weak factor loadings. Cross-loadings blur the distinction between factors, making it unclear which factors are truly represented by the observed variables. Weak factor loadings, on the other hand, can reduce the reliability and validity of the factor structure(Zhang et el., 2015). Researchers need to address these issues by refining the measurement items, revising the factor structure, or considering alternative approaches to item rotation.

Sample size and statistical power can pose challenges in item rotation. Insufficient sample size may lead to unstable or unreliable factor structures, as the estimation of factor loadings becomes less accurate. Small sample sizes can also limit the detection of meaningful patterns or relationships among variables, resulting in inconclusive or biased results Rese (Zhang et el., 2015). The determination of an appropriate sample size for factor analysis is a nuanced endeavour that hinges on several methodological, statistical, and contextual considerations. While there's no one-size-fits-all answer, various guidelines and principles have been posited in academic literature to guide researchers in this complex decision-making process. One commonly cited heuristic suggests a minimum ratio of 5-10 subjects per variable (i.e., item) for factor analysis. Thus, if you have a questionnaire with 20 items, a sample size ranging from 100 to 200 participants might be considered adequate by this guideline (Alordiah, 2015). However, this rule is somewhat arbitrary and can be influenced by the complexity of the data structure, communalities, and the magnitude of the factor loadings. Before conducting factor analysis, researchers often assess the sampling adequacy using the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO).

A KMO value above 0.60 is generally deemed acceptable, indicating that the data is suitable for factor analysis. Another criterion revolves around the eigenvalues, wherein factors with eigenvalues greater than 1 are retained. However, this method doesn't necessarily provide insights into sample size determination but rather aids in factor extraction. If the factor model is complex, with a large number of factors or items, a larger sample size may be warranted to ensure stability and robustness in factor extraction and interpretation. The type of factor analysis—whether exploratory or confirmatory—also influences sample size considerations. Confirmatory factor analysis (CFA) typically necessitates larger sample sizes than exploratory factor analysis (EFA) due to the predefined nature of the model in CFA. In statistical inference, considerations related to effect size, statistical power, and desired confidence intervals can also inform sample size determination. Conducting a priori power analysis can provide empirical insights into the requisite sample size based on expected effect sizes and desired levels of statistical power. Researchers need to carefully consider the sample size in their study design to minimize the limitations associated with small samples.

Implications

This paper has important practical implications for researchers and practitioners involved in scale development. Researchers should carefully consider the selection of item rotation methods based on the research objectives, theoretical framework, and nature of the observed variables. The choice between orthogonal and oblique rotations depends on factors such as the expected relationships among factors, the presence of cross-loadings, and the complexity of the construct being measured (de Castro et el., 2015). Researchers should also pay attention to the interpretation of factor loadings, pattern matrices, and addressing issues such as cross-loadings and residual correlations.

Item rotation plays a crucial role in enhancing scale validity by ensuring that the observed variables adequately represent the underlying constructs (Allo et el., 2021). By addressing content validity, factor structure validity, discriminant validity, and convergent validity through item rotation, researchers can develop more robust and reliable measurement scales. Furthermore, item rotation is essential for achieving scale interoperability, particularly in cross-cultural research, by assessing cross-cultural validity, conducting invariance testing, and evaluating the generalizability of rotated factor structures.

This paper contributes to both theory and practice in the field of scale development. Theoretical contributions include providing a comprehensive understanding of the theoretical foundations of item rotation, the principles of factor analysis, and the differences between exploratory and confirmatory factor analysis. The exploration of orthogonal and oblique rotation methods, along with the associated theoretical considerations, further enriches the knowledge base in scale development.

In terms of practical contributions, this paper offers guidelines for researchers engaged in scale development, highlighting the importance of item rotation for enhancing scale validity and interoperability. The practical implications provided can assist researchers in making informed decisions regarding item rotation methods and addressing specific challenges, such as cross-loadings and residual correlations.

Conclusion

This paper explored the theoretical foundations and strategies for item rotation in scale development. The importance of scale development in social sciences, the role of factor analysis, and the need for item rotation to enhance scale validity and interoperability were discussed. Theoretical considerations in item rotation, such as factor structure interpretation, factor variance explained, factor loadings, and simple structure, were examined in detail. The paper also, delved into the differences between exploratory and confirmatory factor analysis and explored the types of rotation methods, including orthogonal and oblique rotations. Furthermore, the article discussed the implications of item rotation for scale development and measurement theory, highlighted the significance of scale validity and item rotation in establishing content validity, factor structure validity, discriminant validity, and convergent validity. Additionally, The paper examined the role of item rotation in achieving scale interoperability, particularly in cross-cultural research, and the importance of invariance testing and generalizability of rotated factor structures.

Future Research Recommendations

To advance the field of item rotation and scale development, several future directions and research recommendations can be considered:

1. Further research can examine how different item rotation methods and strategies impact the psychometric properties of measurement scales, including reliability, validity, and sensitivity. This research can provide guidance on selecting the most appropriate item rotation technique for specific research contexts.
2. Future studies should focus on replicating factor structures across diverse samples and populations to evaluate the generalizability of rotated factor structures. This will contribute to establishing the robustness and cross-cultural validity of measurement scales.
3. Researchers can explore the integration of item rotation with other analysis methods, such as item response theory or structural equation modeling. This integration can enhance the precision and efficiency of scale development and improve the understanding of the underlying constructs.
4. Research efforts should focus on developing strategies to address the limitations associated with small sample sizes in factor analysis. This can include exploring robust estimation methods or conducting simulation studies to determine the minimum sample size requirements for reliable item rotation.

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