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Impact of Conditions which Affect Exploratory Factor Analysis

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Executive Summary

Some things cannot be observed directly and must be inferred from multiple indirect measurements, such as human experiences accessed through a variety of survey questions. Exploratory Factor Analysis (EFA) provides a data-driven method to optimally combine these indirect measurements to infer some number of unobserved factors. Ideally, EFA should identify how many unobserved factors the indirect measures help estimate (factor extraction), as well as accurately capture how well each indirect measure estimates each factor (parameter recovery).

However, many factor extraction techniques exist, and the field lacks consensus on the most accurate approach. In my first simulation study, I primarily evaluated how accurately four standard techniques (BIC, eigenvalue thresholds, RMSEA, and Parallel Analysis) perform factor extraction. This study also identified the conditions which most influence factor extraction accuracy. In my second study, I examined how commonly encountered conditions in survey analysis, such as sample size, item quality, and repeated measurements, affect parameter recovery.

The results of these studies support several best practice recommendations for survey analysis. First, the most commonly used technique, eigenvalue thresholds, provides the least accurate results and should be avoided. Instead, analysts should utilize the less popular but much more accurate RMSEA approach. Second, while the common belief is that repeated measurements should hurt EFA, the results of these studies suggest repeated measurements strongly enhance the effectiveness of EFA.

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Kevin Krost, Heather Wojton, Daniel Porter, and Stephanie Lane

Institute for Defense Analyses

SUMMARY

Some things cannot be observed directly and must be inferred from multiple indirect measurements, for example, human experiences accessed through a variety of survey questions.

Exploratory Factor Analysis (EFA) provides a data-driven method to optimally combine these indirect measurements to infer some number of unobserved factors.

Ideally, EFA should identify **how many** unobserved factors the indirect measures help estimate (factor extraction), as well as accurately capture **how well** each indirect measure estimates each factor (parameter recovery).

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In my second study, I examined how commonly encountered **conditions** in survey analysis, such as sample size, item quality, and repeated measurements, affect **parameter recovery**.

The results of these studies support several **best practice recommendations** for survey analysis.

First, the most commonly used technique, **eigenvalue thresholds**, provides the **least accurate** results and should be avoided. Instead, analysts should utilize the less popular but **much more accurate RMSEA** approach.

Second, while the common belief is that **repeated measurements** should hurt EFA, the results of these studies suggest repeated measurements strongly **enhance the effectiveness** of EFA.

IMPORTANT TERMS

- **Exploratory Factor Analysis (EFA)** – A statistical method which provides a measure of the strength that an item measures an unobserved trait or skill.
- **Monte Carlo Simulation Study** – A computer-intensive method to evaluate a statistical method by generating and analyzing data many times (i.e., 1,000)
- **Item Quality (Communality)** – The variance each item accounts for across all factors, ranging from 0 to 1 with higher values desired
- **Bayesian Information Criterion (BIC)** – A statistic which measures the amount of error in a model and values closest to -∞ are desired
- **Eigenvalue** – The amount of variance attributed to a latent factor where values greater than 1 indicate the number of factors to extract
- **Root Mean Squared Error of Approximation (RMSEA)** – A statistic which measures error and values closest to 0 are desired
- **Parallel Analysis** – A simulation method which generates random data with the same number of observations and variables then compares it to the true data until the results converge
- **Parameter Recovery** – The difference between a true statistic and an estimated statistic which can be calculated using several statistics
- **Root Mean Squared Error (RMSE)** – A measure of model error which only takes on positive values
- **Mean Absolute Error (MAE)** – A measure of average model error which only takes on positive values
- **Bias** – A measure of model error which can be positive or negative and can indicate over- or under-estimation

METHODS

Monte Carlo simulation study to evaluate EFA

- Data simulated and analyzed 1,000 times then averaged across the replications

Fully crossed to evaluate interactions between conditions

- 4 * 3 * 3 conditions = 36 unique combinations

Software used was R and Microsoft Excel

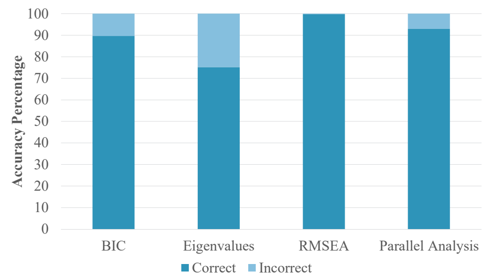
- Psych package was used for data generation and analysis
- Excel used for data organization and visualization

Conditions values are summarized in the following table

Conditions	Levels of Condition			
Total Sample Size	24	48	144	384
Item Quality	0.3	0.5	0.8	
Number of Measurements	1	3	6	

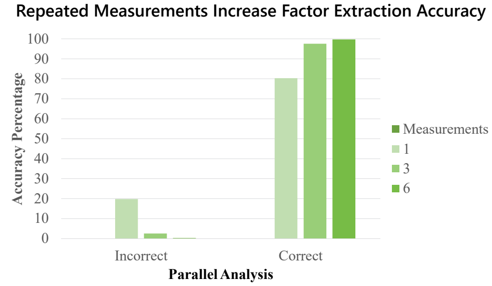
FACTOR EXTRACTION RESULTS

RMSEA Is Most Accurate for Factor Extraction



RMSEA was the most accurate method for determining the number of factors to extract, where the correct number of factors resulted in the smallest amount of error. Using eigenvalues > 1 was the least accurate method.

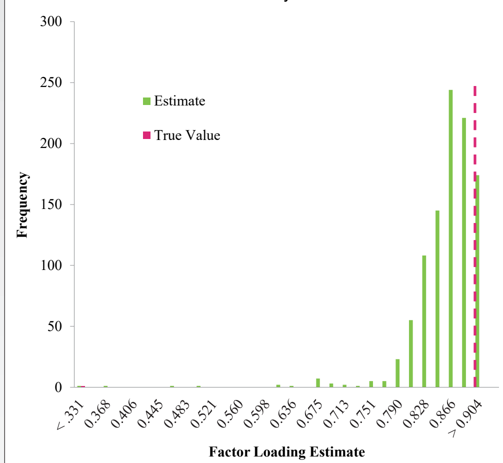
Repeated Measurements Increase Factor Extraction Accuracy



Parallel Analysis was the second most accurate factor extraction method, and repeated measurements was the strongest predictor of its accuracy. There was a large increase in accuracy going from 1 to 3 measurements, and almost perfect accuracy with 6 measurements.

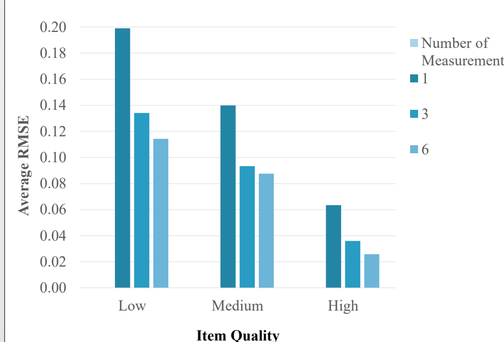
PARAMETER RECOVERY RESULTS

Parameter Recovery Illustration



The true estimate in this situation was 0.897, indicating a high quality item. Most estimated values were lower than the true value, but fairly accurate given the particular conditions of this replication.

Item Quality and Repeated Measures Improve Parameter Recovery



Item quality and the number of measurements were the strongest predictors of average model error. The model error was minimized as item quality and the number of repeated measurements increased. Overall, model error was minimal.

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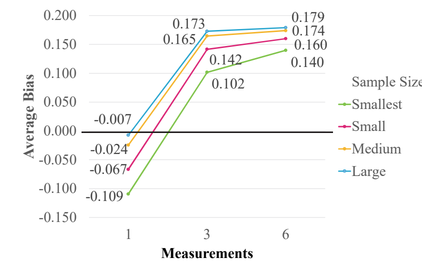
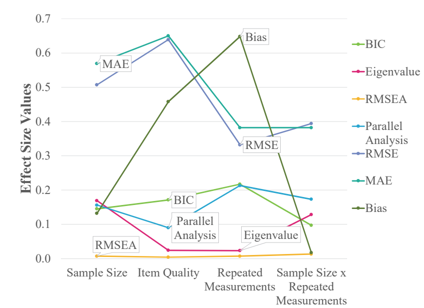
Bias Increases with Repeated Measures



Model bias was minimal when there was a single measurement, but somewhat larger when measurements increased. There were sizable differences between the smallest and largest sample sizes, but the effect was less noticeable among larger sample sizes.

Importance of Conditions Across Outcome Measures



Study Conditions with Largest Effects

The importance of the condition depended on the outcome and study in question. Item quality was the strongest predictor for MAE and RMSE, while repeated measurements was the strongest predictor of BIC and parallel analysis extraction methods.

DISCUSSION

These studies offer several insights about exploratory factor analysis:

1. Researchers should rely less on eigenvalue cutoff rules when choosing the number of factors for EFA.
2. RMSEA is the most accurate factor extraction indicator and should be used more. Parallel Analysis was the second most accurate factor extraction method.
3. Repeated measurements appear to have a positive effect on EFA and should be explored more.
4. Sample size is less important than previously thought, so small sample sizes may be viable when conducting EFA.
5. Item quality is important for parameter recovery, but less important for accurate factor extraction.
6. Researchers should use multiple methods to validate their factor solutions, to account for potential discrepancies among the results.

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14. ABSTRACT

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