# Simulations and Applications of EFA and MFA Methods Applied to ADNI Cognitive Data

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## Overview

We compare Multiple Factor Analysis (MFA) and Exploratory Factor Analysis (EFA) through both application to the ADNI neuropsychological battery and simulations. We then suggest methods for further longitudinal analyses of MFA factor loading trajectories.

## Background

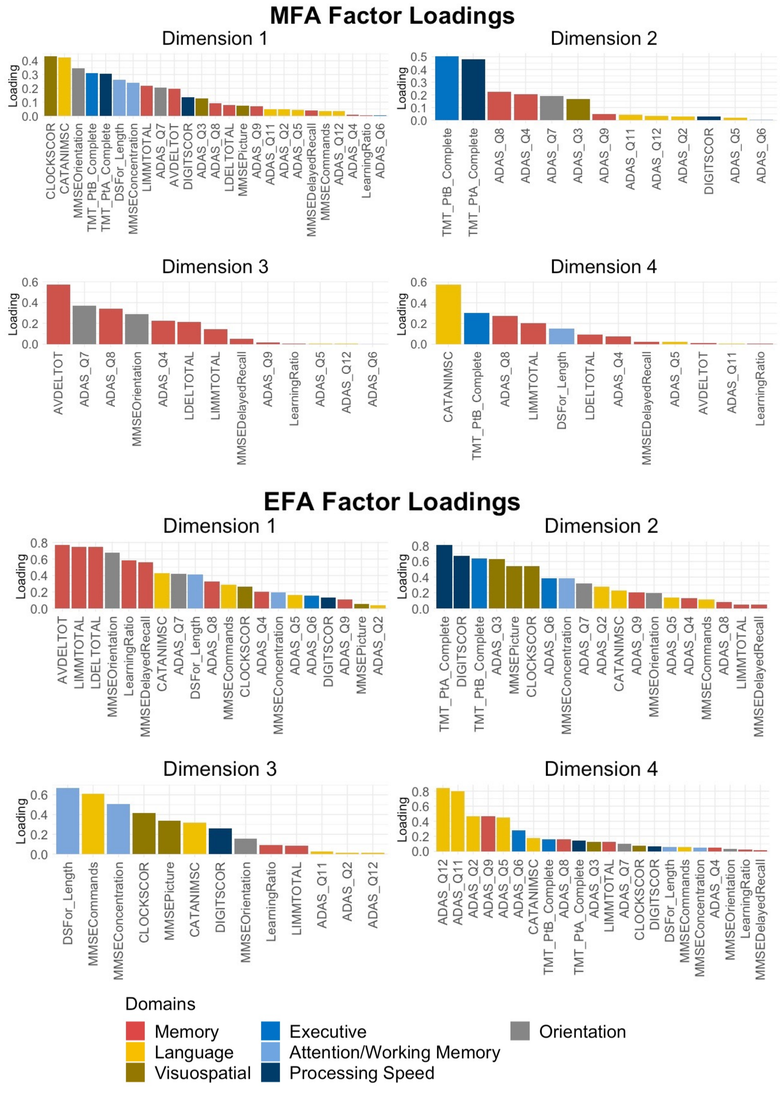
- Factors and related composite scores can be used to monitor longitudinal changes in patient trajectories, identify and validate associations with biomarkers, describe patterns across domains, and predict time to conversion to AD.
- These factors are usually constructed with exploratory factor analysis (EFA) for cognitive datasets.
- However, this method does not take the clustered nature of the cognitive tests by domain into account. Multiple factor analysis (MFA), an extension of EFA, attempts to fix this limitation, and a comparison of these two methods is needed.

## Study Design and Methods

- Both EFA (exploratory factor analysis) and MFA (multiple factor analysis) were conducted on cognitive score data for Alzheimer's patients from the Alzheimer's Disease Neuroimaging Initiative (ADNI).
    - A four-factor solution was chosen based on parallel analysis results
- Simulations were then conducted to compare the performance of these methods on similar data, using average correlations between true and estimated loadings and root mean squared error as outcomes.
    - Datasets of varying sample sizes were generated from a four-factor model with significant loadings on 10, 5, 2, and 2 variables, respectively.
    - True and estimated factor loadings were matched based on the Tucker index of factor congruence
- Individual factor loadings from MFA can then be extracted and used as outcomes in function on scalar regression (FOSR) models to ascertain whether differences in loading trajectories exist among diagnoses.

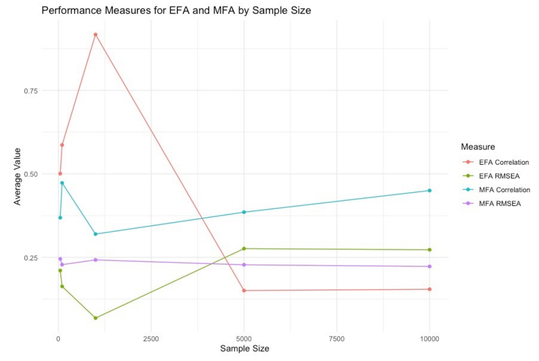
## Factor Analysis Application

- The largest set of variables, memory, dominates the first axis in EFA because it is more heavily represented in the data.
- MFA balances the groups and results in a factor structure that better separates the cognitive domains.




## Simulation and FOSR

- Preliminary simulations suggest that estimated MFA loadings are more correlated with true loadings and result in lower RMSEA for large sample sizes.
- Future work will examine how the relationship between these estimated and true loadings change with varying amounts of missing data and increasing correlations between factors.




- While individual scores from EFA are not uniquely determined due to factor indeterminacy, individual factor scores from MFA can be extracted and plotted over time. For example, function on scalar regression shows that for dimensions 3 and 4, loading trajectories for early and late onset AD subjects are significantly different.

## Conclusions

- MFA prevents more heavily represented tables from dominating the first factor, results in both lower RMSEA and higher correlations with true loading values when applied to large datasets, and is better suited for future factor score analyses when compared to EFA.

## References

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