

# Colorado Family Support Assessment, 2.0


## Multiple Domain Analysis

Submitted to the Office of Early Childhood and Family Resource Center Association

June 21, 2017



Family Resource  
Center Association



# Colorado Family Support Assessment, 2.0

## Multiple Domain Analysis

For more information, please contact:

Melissa Richmond, PhD  
Director of Research and Evaluation  
OMNI Institute  
899 Logan Street, Suite 600, Denver, CO 80203  
[mrichmond@omni.org](mailto:mrichmond@omni.org); 303-839-9422, Ext. 166  
[www.omni.org](http://www.omni.org)

**OMNI Contributors:** Sara Bayless, PhD, Shelby Jones, MA.

# Table of Contents

- Introduction and Purpose ..... 1
- Overview of Method ..... 1
- Summary of Findings and Recommendations ..... 1
- Technical Report ..... 3
  - Data Quality Review ..... 3
  - Exploratory Factor Analyses: Analytic Approach and Results..... 4
  - Confirmatory Factor Analyses: Analytic Approach and Results..... 8
- References ..... 8

# Figures and Tables

- Figure 1. CFSA 2.0, Part A Factor Structure ..... 2
- Table 1. Domains Included in Analyses by Analytic Step ..... 5
- Table 2. Sample Sizes Used in Exploratory Factor Analysis Steps with Listwise Case Deletion vs. Full Information Maximum Likelihood ..... 6
- Table 3. Model Fit for One- and Two-Level Exploratory Factor Analyses..... 7
- Table 4. Confirmatory Factor Analysis Results for Recommended Factor Structure of CFSA 2.0, Part A. ... 8

# INTRODUCTION AND PURPOSE

OMNI Institute conducted a factor analysis to identify the underlying factor structure of the domains included in Part A of the Colorado Family Support Assessment (CFSA 2.0). The CFSA 2.0 is a three-part tool used by the Family Resource Center Association (FRCA) to assess outcomes for families receiving family development services from its member Family Resource Centers (FRCs). Part A assesses family self-reliance in 14 domains (e.g., housing, transportation, employment), with indicators for each domain ranging from 1 (in crisis) to 5 (thriving). Part B is the Protective Factors Survey (PFS), and Part C identifies areas in which families would like to set goals and their readiness to change in those areas. This report describes results from factor analyses conducted on Part A, and the resulting recommended factor structure that can be used to monitor the progress of families who are administered the tool.

## OVERVIEW OF METHOD

Factor analysis is a data reduction technique that examines the relationships among measured variables (in this case, each CFSA 2.0, Part A domain). Results help identify whether the measured variables are based on underlying ‘factors’ (for example, economic self-sufficiency). Measurement of underlying factor(s) can efficiently provide information on whether programs are impacting multiple dimensions of an outcome rather than only examining each component individually. Prior to conducting the factor analysis, a data quality review examined variability of responses within each domain; similarities and differences among the individual FRCs; and the amount of missing data in each domain.

Families included in the analyses were those who completed a baseline CFSA 2.0 between July 1<sup>st</sup>, 2015 and April 17<sup>th</sup>, 2017 (n = 3,564). Data came from families served by 24 FRCs across Colorado. Thirteen of the 14 domains of the CFSA 2.0, Part A were included in the analyses: *Income, Employment, Housing, Transportation, Food Security, Child Care, Child Education, Adult Education, Cash Savings, Debt Management, Health Coverage, Physical Health, and Mental Health*. The *Substance Use* domain was excluded from analyses due to insufficient variability in responses across families.

## SUMMARY OF FINDINGS AND RECOMMENDATIONS

The full set of results from model testing is presented in the technical report that follows this summary. In brief, the factor analyses yielded three major findings with respect to the factor structure of the CFSA 2.0, Part A:

- Across models, *Income, Employment, Housing, Transportation, Food Security, Adult Education, Cash Savings, and Health Coverage* consistently pulled together into one factor, suggesting that these components are measuring a single underlying construct. Given the content of the domains that contribute to this factor, we refer to it as *Economic Self-Sufficiency* and recommend creating an 8-domain composite scale by combining the domains into a single scale.
- Across models, *Physical Health* and *Mental Health* consistently pulled together into one factor, suggesting that these components are measuring a single underlying construct. Given the content of the domains that contribute to this factor, we refer to it as *Health*, and recommend creating a 2-domain composite scale by combining ratings on these two domains into a single scale.
- Three domains, *Debt Management, Child Education, and Child Care*, were inconsistent across models. As such, we recommend that these domains are each analyzed separately.

Results of analyses also indicated that although there is some variation between FRCs in how domains are scored, these differences do not significantly impact the factor structure of the CFSA 2.0, Part A. This is a positive finding and suggests that the structure of the tool is the same across communities. Therefore, the recommended factor structure of the *Economic Self-Sufficiency* and *Health* composite scales can be used across FRCs. The recommended factor structure is depicted in Figure 1.

Figure 1. CFSA 2.0, Part A Factor Structure

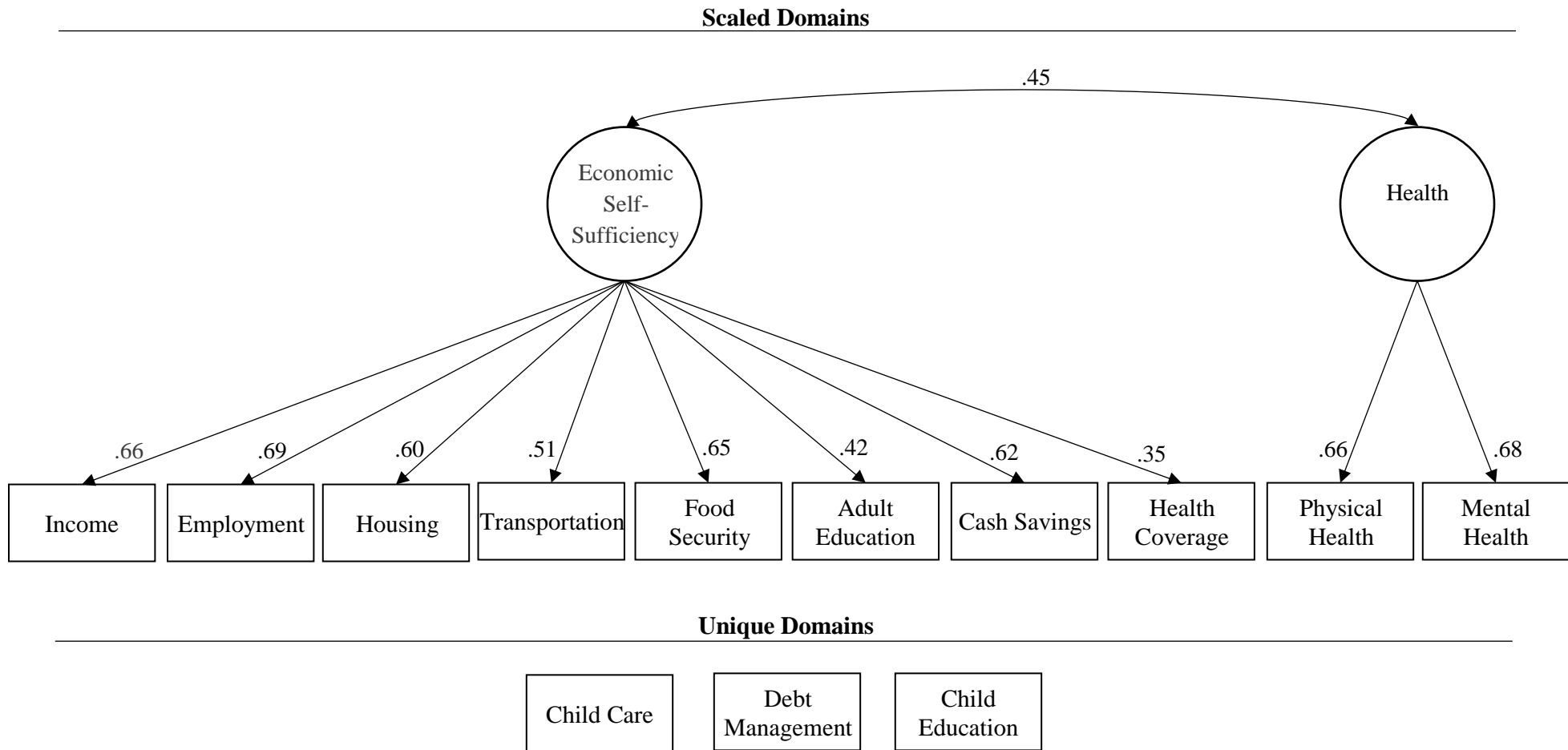


Figure 1. Standardized Results of the Confirmatory Factor Analysis with the Recommended Factor Structure of the CFSA 2.0, Part A. *Note:* Factors are represented in circles, and domains are represented in rectangles. Factor loadings reflect how strongly the factor represents each domain. The factor correlation reflects how strongly the factors are related to each other

# TECHNICAL REPORT

This technical report provides a detailed discussion of the analytic procedures that contributed to the factor analysis of the CFSA 2.0, Part A, as well as the results of these analytic procedures. The report is structured in three sections: (1) Data Quality Review, (2) Exploratory Factor Analyses: Analytic Approach and Results, and (3) Confirmatory Factor Analyses: Analytic Approach and Results.

## Data Quality Review

To inform OMNI's approach to the factor analysis, a data quality review was undertaken to examine: 1) variability of responses within each domain, including statistical indicators of the domain's distributional qualities (e.g., skewness and kurtosis); 2) similarities and differences among the individual Family Resource Centers (FRCs); and 3) the amount of missing data in each domain.

The results from the data quality review informed key decisions regarding the analytic plan for the factor analysis. Below, we document findings from each component of the data quality review.

## DOMAIN CONSIDERATIONS

- The *Substance Abuse* domain displayed very little variability; 88% of participants with valid responses indicated the highest level of functioning (i.e., a score of 5). This indicates that the domain is not meaningfully differentiating between respondents, and therefore we recommended that it be excluded from all analyses. As a result, factor analyses were conducted with a maximum of 13 (rather than 14) domains.
- The distribution of the *Income* domain was also a concern, as responses were skewed towards the lower end of the scale (i.e., a preponderance of 1s and 2s), which indicates a non-normal distribution. Given the population that Family Resource Centers serve, it is likely that this accurately reflects individual circumstances of income, rather than an issue with the item differentiating between individuals (as with the *Substance Abuse* domain). A natural log transformation was used to correct the positive skewness, and a value of 1 was subsequently added to all scores to move the bottom range of the scale from 0 to 1. Note that transformations and adding a constant influences the shape of the distribution to improve factor analysis results, but does not change the relative relationship between variables.
- The *Employment*, *Child Care*, and *Child Education* domains allow for 'not applicable' responses. Not applicable is used for a) *Employment* when all adults in the family are not employable, b) *Child Care* when families do not have children under 12 years old or the family is adequately able to care for children and does not need child care; and c) *Child Education* when all children in the family are not school-aged or they have earned a GED. Approximately 9%, 51%, and 39% of families indicated 'not applicable' to the *Employment*, *Child Care*, and *Child Education* domains, respectively. To account for the fact that responses in these domains are purposefully missing for some respondents, a series of steps were adopted to estimate a factor structure with and without these domains (see Table 1, below, for further detail).
- Initial data exploration did not indicate that the *Transportation* domain needed to be transformed, as the skewness value of -1.328 was within the acceptable range of -2 and 2. However, results from the initial exploratory factor analyses (EFAs) indicated that transportation was not hanging well with the factors (i.e., did not have consistently strong loadings with any factors), so transformation was explored as a possible remedy. Responses were skewed towards the upper end of the scale (i.e., a preponderance of 4s and 5s), so an exponential transformation was used. Subsequent EFA results indicated that the transformed transportation variable performed better in that factor

loadings were more consistent and interpretable. Therefore, all analyses reported here include the transformed version of the transportation domain.

## SAMPLE SIZE CONSIDERATIONS

Each domain was reviewed for potential missing data concerns. A large number of respondents (3,564) completed a baseline CFSA between July 1<sup>st</sup>, 2015, and April 17<sup>th</sup>, 2017. However, missing data affects the number of respondents that are available for any given analysis. Listwise case deletion indicates that 28% of the sample had a valid response for every domain item. The majority of missing data results from the ‘not applicable’ responses, which are valid response options for the *Employment*, *Child Care*, and *Child Education* domains. As such, the majority of missing data may result from proper administration of the measure. A small proportion of missing data results from instances in which family workers were unable to obtain sufficient information to appropriately score a domain during the interview with the family (coded as ‘not enough information’); this type of missing data is to be expected in applied settings and generally accounts for a small proportion of the data. Specifically, the range of missing values due to ‘not enough information’ for the 14 domains was 1.1% to 9.1%, with an average of 3.7% missing across the domains.

However, missing data is a statistical concern because it can bias, and therefore reduce the accuracy of, analyses. As noted in more detail below, the influence of the high presence of missing data in this sample due to ‘not applicable’ responses was explored by removing and adding relevant domains that had this response option to the factor analysis models. To account for the influence of the smaller amounts of missing data due to ‘not enough information’, we compared the results from standard EFAs to results from factor analyses using a statistical approach known as full information maximum likelihood. This approach to missing data allows all respondents who have at least one valid response on a domain to be included in the analyses. When compared to traditional approaches to missing data, which would require participants to have a valid response on all domains, this increases the sample size; comparison of the traditional approach (i.e., listwise case deletion) and the approach using full information maximum likelihood determines whether the missing data due to ‘not enough information’ bias the results of the factor analyses, and thus needed to be accounted for statistically.

## FAMILY RESOURCE CENTER (FRC) CONSIDERATIONS

The data quality review revealed that there were consistent, significant differences between FRCs across domains. First, some FRCs had average (mean) domain ratings that were consistently higher or lower than other FRCs. Specifically, families from one FRC scored significantly higher than average on 8 of the 14 domains and families from another scored significantly higher than average on 7 of the 14 domains. In contrast, families from a third FRC scored significantly lower than average on 9 of the 14 domains. Second, results suggested that, although small, there may be some ‘clustering’ of responses at the FRC level, indicating that some of the variance in responses may be due to similarities in families served by centers (i.e., intraclass correlation coefficients (ICCs) for each domain range from .07 to .40). Differences in family ratings across centers may reflect the different populations that FRCs serve, or they may be the result of systematic differences in how staff in different FRCs administer the tool. We compared the results from one-level and two-level standard EFAs to determine whether the differences in response patterns at the level of the FRC influenced the factor structure, and thus needed to be accounted for statistically.

## Exploratory Factor Analyses: Analytic Approach and Results

Given the domain, sample size, and FRC considerations, we conducted three phases of EFAs. The methods used in each phase are discussed in detail.



## PHASE 1: EXPLORING THE INFLUENCE OF DOMAINS ON FACTOR STRUCTURE

EFA were conducted using a Principal Axis Factor approach in the statistical software SPSS. Specifically, a series of EFAs were conducted, with six variations on the domain used, and subsequently the sample (or subsample) used for the analyses. These are detailed below, and depicted in Table 1.

1. EFAs were conducted for domains that do not have “Not Applicable” as a response option (i.e., excluding the Employment, Child Care, and Child Education domains), using the full sample;
2. EFAs were conducted with the Employment domain, using the sub-sample that had a valid response for this domain;
3. EFAs were conducted with the Child Care domain, using the sub-sample that had a valid response for this domain;
4. EFAs were conducted for the Child Education domain, using the sub-sample that had a valid response for this domain;
5. EFAs were conducted with the Child Care and Child Education domains, using the sub-sample that had valid responses for both these domains; and
6. EFAs were conducted with the Child Care, Child Education, and Employment domains, using the sub-sample that had valid responses for all three of these domains.

Table 1. Domains Included in Analyses by Analytic Step

CFSA 2.0, Part A Domain	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
Income	X	X	X	X	X	X
Employment		X				X
Housing	X	X	X	X	X	X
Transportation	X	X	X	X	X	X
Food Security	X	X	X	X	X	X
Adult Education	X	X	X	X	X	X
Cash Savings	X	X	X	X	X	X
Debt Management	X	X	X	X	X	X
Health Coverage	X	X	X	X	X	X
Physical Health	X	X	X	X	X	X
Mental Health	X	X	X	X	X	X
Child Care			X		X	X
Child Education				X	X	X
Substance Abuse*						

\*All analyses excluded the *Substance Abuse* domain due to issues with the variable identified in the data quality review.

All of the models outlined above were estimated using two methods of rotation: orthogonal rotations, which assumes that factors are uncorrelated, and oblique rotations, which assumes that factors are correlated. Varimax and promax versions were used for orthogonal and oblique rotations, respectively. The number and nature of underlying factors were examined using an eigenvalue criterion of 1.0 or greater; however, if factors had an eigenvalue of .90 or higher, the factor loadings for these solutions were also considered, and the best factor solutions were identified by factor loadings across all domains. At the item level, domains were considered to contribute to a factor if they had a loading of .32 or higher. Domains with a loading of .32 or higher on more than one factor were considered cross-loading. Cross-loadings are not desirable because they indicate that the factor does not clearly define a distinct cluster of variables. Domains without any loadings of .32 or higher were considered to not load, which suggests that they do not contribute to any of the factors identified in the results (Yong & Pearce, 2013). Results from the orthogonal and oblique rotations were examined to identify which solution was the most conceptually sound (i.e., whether the domains that loaded onto the

resulting factors made conceptual sense) and parsimonious (i.e., included few or no domains that cross-loaded across factors).

Results across the 12 models (six using orthogonal rotation; six using oblique rotation) suggested that the oblique rotations generally fit the data better; across the 12 models, there were five instances of domains cross-loading onto factors for the orthogonal models, and one instance of a domain cross-loading onto factors for the oblique models. This suggests that the factors that result from the variety of domain combinations are consistently correlated with one another, and therefore the models that allow for this correlation are a better fit. As such, oblique models were interpreted and used in subsequent phases of analyses.

Second, results across models suggested that a two-factor model fits the data best, with the *Income, Employment, Housing, Transportation, Food Security, Adult Education, Cash Savings, and Health Coverage* domains loading consistently onto one factor (referred to as Economic Self-Sufficiency), and the *Physical Health* and *Mental Health* domains loading consistently onto another factor (referred to as Health). The *Child Care* and *Child Education* domains did not consistently load onto one factor, and did not load onto their own factor. The *Debt Management* domain did not consistently load onto the same factor across models; the most consistent factor that it loaded onto was the factor made up of *Physical Health* and *Mental Health*, which was determined not to be conceptually sound.

## PHASE II: EXPLORING THE INFLUENCE OF MISSING DATA ON FACTOR STRUCTURE

To examine whether the missing data due to ‘not enough information’ biased the results of the factor analyses, EFAs were replicated using a full information maximum likelihood (FIML) approach to account for missing data. Use of FIML estimation has the desirable effect of increasing the sample size for analyses, thus increasing the statistical power of the factor analyses (in this case, statistical power is the ability to accurately detect the true number of underlying factors). Table 2 presents the sample sizes across Steps 1-6 using the listwise case deletion and FIML approaches for the oblique models.

**Table 2. Sample Sizes Used in Exploratory Factor Analysis Steps with Listwise Case Deletion vs. Full Information Maximum Likelihood**

Method	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
Listwise Case Deletion <i>n</i>	2881	2636	1392	1718	1056	1056
FIML <i>n</i>	3560	3205	1658	2012	1223	1164

Results across these twelve models (6 oblique models using listwise case deletion; 6 oblique models using FIML) indicate that there were very few differences between the listwise case deletion and FIML solutions. Across all Steps, there were no differences in the number of factors provided by the solutions. Further, for Steps 1, 3, 5, and 6, there were no differences in how domains loaded onto factors (while factor loading values varied between the listwise case deletion and FIML models, these slight differences did not change the interpretation of any of the domains with respect to factor structure). In Step 2, *Housing* cross-loaded onto two factors in the FIML solution, whereas it loaded onto one factor in the listwise case deletion solution; additionally, *Transportation* didn’t load onto any factors in the listwise case deletion solution, whereas it loaded onto one factor in the FIML solution. In Step 4, *Transportation* didn’t load onto any factor in the listwise case deletion solution, whereas it loaded onto one factor in the FIML solution. The minimal differences that occurred between the listwise case deletion and FIML solutions suggest that missing data due to ‘not enough information’ did not bias the results of the factor analysis in any meaningful way.

## PHASE III: EXPLORING THE INFLUENCE OF FRCs ON FACTOR STRUCTURE

To examine whether the differences in response patterns at the level of the FRC influence the factor structure, the EFAs identified above were replicated in two-level models. The two-level models were implemented so that FRCs were at level 2, and respondents were nested within FRCs at level 1. This approach adjusts the standard errors used in all model estimates to account for the bias that might otherwise occur due to the differences in mean and variance across FRCs identified in the data quality review. Substantial differences between the results obtained from one- and two-level models would suggest that the two-level model solutions should be retained for the results to be valid across all respondents and FRCs. In contrast, lack of substantial differences between the results would suggest that the standard approach is sufficient to obtain accurate results.

Multilevel model results were conducted in Mplus, as SPSS does not have the capacity to conduct two-level EFAs. Based on results from Phase I, which indicated that oblique rotations fit the data better, oblique rotations were used for the multi-level EFA. The specific type of oblique rotation (promax) that was used in previous analyses in SPSS could not be used for the multilevel models, as Mplus does not allow promax oblique rotation for multi-level models. Instead, the default setting in Mplus for multi-level models is geomin rotation. Therefore, in addition to conducting six two-level exploratory factor analysis models using the geomin rotation, we also conducted six one-level exploratory factor analysis models using the geomin rotation. This enables us to make direct comparison between one- and two-level models using the same rotation method; if we had made comparisons between one-level models with promax rotation and two-level models with geomin rotation, the type of rotation would have been a confounding factor.

Comparisons between models were based on three model fit indices, as recommended by Kline (2005), including the comparative fit index (CFI), the standardized root mean square residual (SRMR) and the root mean square error of approximation (RMSEA). With respect to CFI, higher values are better; for SRMR and RMSEA, lower values are better. Decisions about whether model fit indicators support adequate model fit were based on established guidelines, which include: CFI values of greater than .90, SRMR values of .08 or lower, and RMSEA values of .07 or lower (Hu and Bentler, 1999; Steiger, 2007). Although the chi-square test is another common model fit index, it was not included given that this test is very sensitive to sample size, and the current models were estimated with relatively large sample sizes (i.e., greater than 1,000).

Model fit values are presented in Table 3. Results indicate that across all three indicators, the one- and two-level models both offer adequate model fit (i.e., all fit indices were within the desired ranges). Further, there is not a substantial difference in model fit between the one- and two-level models: specifically, differences in CFI values range from .00 to .04; there are no differences in SRMR values; and differences in RMSEA range from .00 to .02. This suggests that the differences in response patterns at the level of the FRC do not substantially influence the factor structure, and thus do not need to be accounted for statistically through a two-level model; the one-level model is sufficient.

**Table 3. Model Fit for One- and Two-Level Exploratory Factor Analyses**

	One-Level Models			Two-Level Models		
	CFI	SRMR	RMSEA	CFI	SRMR	RMSEA
<b>Step 1</b>	.93	.03	.07	.89	.03	.05
<b>Step 2</b>	.97	.02	.05	.95	.02	.04
<b>Step 3</b>	.98	.03	.05	.96	.03	.05
<b>Step 4</b>	.95	.03	.05	.95	.03	.04
<b>Step 5</b>	.95	.03	.05	.96	.03	.04
<b>Step 6</b>	.95	.03	.05	.95	.03	.05

## Confirmatory Factor Analyses: Analytic Approach and Results

Finally, given the results from the three phases of EFAs, a single confirmatory factor analysis (CFA) model was estimated. CFAs differ from EFAs in that a factor structure is imposed on the data, and model fit indices are used to determine whether that select factor structure adequately fits the data. The factor structure selected for the CFA was based on the cumulative results of the three phases of EFAs; a one-level model with two factors, one representing economic self-sufficiency, and one representing health, was estimated (see Table 4). The same model fit indices used to assess model fit in the one- and two-level EFA models (i.e., CFI, SRMR and RMSEA) were used to evaluate model fit of the CFA. Results support adequate model fit (CFI=.91, SRMR= .05, and RMSEA=.07). Additionally, the factor loadings of each domain were examined, and all factor loadings were significant at  $p < .001$  (see Table 4), indicating that each of the factors are well defined by its items. Finally, the covariance between the two factors was examined, and results indicated that although the two factors are unique, they are significantly and positively related to one another ( $b = .445$ ,  $SE = .02$ ,  $p < .001$ ). This is consistent with the conclusions of Phase I of the EFAs, in which the oblique rotations generally fit the data better, indicating that the underlying factors were related.

Table 4. Confirmatory Factor Analysis Results for Recommended Factor Structure of CFSA 2.0, Part A.

CFSA 2.0, Part A Domain	Standardized Factor Loadings	
	Factor 1: <i>Economic Self-Sufficiency</i>	Factor 2: <i>Health</i>
Income	.655	-
Employment	.687	-
Housing	.595	-
Transportation	.512	-
Food Security	.651	-
Adult Education	.419	-
Cash Savings	.615	-
Health Coverage	.349	-
Physical Health	-	.656
Mental Health	-	.679

*Note:* – indicates that the item was not estimated on that factor. All factor loadings are significant at  $p < .001$ .

## REFERENCES

- Hu, L.T. and Bentler, P.M. (1999), "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives," *Structural Equation Modeling*, 6 (1), 1-55.
- Kline, R.B. (2005), *Principles and Practice of Structural Equation Modeling* (2nd Edition ed.). New York: The Guilford Press.
- Steiger, J.H. (2007), "Understanding the limitations of global fit assessment in structural equation modeling," *Personality and Individual Differences*, 42 (5), 893-98.
- Yong, A. G., & Pearce. S. (2013). A Beginner's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis. *Tutorials in Quantitative Methods for Psychology*, 9(2), 79-94.