Exploratory Factor Analysis

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2012-04-26
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Outline

• Seven stages of applying factor analysis
• Exploratory Factor Analysis (EFA) vs. Confirmatory Factor Analysis (CFA)
• Identify the differences between component analysis and common factor analysis models
• How to determine the number of factors to extract
• How to name a factor

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Chapter 3
Exploratory Factor Analysis

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Exploratory Factor Analysis (EFA)

• Definition
  – Exploratory factor analysis (EFA) is an interdependence technique whose primary purpose is to define the underlying structure among the variables in the analysis.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Exploratory Factor Analysis (EFA)

- Examines the interrelationships among a large number of variables and then attempts to explain them in terms of their common underlying dimensions.
- These common underlying dimensions are referred to as factors.
- A summarization and data reduction technique that does not have independent and dependent variables, but is an interdependence technique in which all variables are considered simultaneously.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
## Correlation Matrix for Store Image Elements

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<th>V₃</th>
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Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Correlation Matrix of Variables After Grouping Using Factor Analysis

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<td>.472</td>
<td>.765</td>
<td>1.00</td>
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</table>

Shaded areas represent variables likely to be grouped together by factor analysis.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Application of Factor Analysis to a Fast-Food Restaurant

Variables

- Waiting Time
- Cleanliness
- Friendly Employees
- Taste
- Temperature
- Freshness

Factors

- Service Quality
- Food Quality

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Factor Analysis Decision Process

• Stage 1: Objectives of Factor Analysis
• Stage 2: Designing a Factor Analysis
• Stage 3: Assumptions in Factor Analysis
• Stage 4: Deriving Factors and Assessing Overall Fit
• Stage 5: Interpreting the Factors
• Stage 6: Validation of Factor Analysis
• Stage 7: Additional uses of Factor Analysis Results
Stage 1: Objectives of Factor Analysis

1. Is the objective exploratory or confirmatory?
2. Specify the unit of analysis.
3. Data summarization and/or reduction?
4. Using factor analysis with other techniques.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Factor Analysis Outcomes

• Data summarization
  – derives underlying dimensions that, when interpreted and understood, describe the data in a much smaller number of concepts than the original individual variables.

• Data reduction
  – extends the process of data summarization by deriving an empirical value (factor score or summated scale) for each dimension (factor) and then substituting this value for the original values.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Types of Factor Analysis

- **Exploratory Factor Analysis (EFA)**
  - is used to discover the factor structure of a construct and examine its reliability. It is *data driven*.

- **Confirmatory Factor Analysis (CFA)**
  - is used to confirm the fit of the hypothesized factor structure to the observed (sample) data. It is *theory driven*.

Stage 2: Designing a Factor Analysis

• Three Basic Decisions:
  2. Design of study in terms of number of variables, measurement properties of variables, and the type of variables.
  3. Sample size necessary.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Factor Analysis Design

• Factor analysis is performed most often only on metric variables, although specialized methods exist for the use of dummy variables. A small number of “dummy variables” can be included in a set of metric variables that are factor analyzed.

• If a study is being designed to reveal factor structure, strive to have at least five variables for each proposed factor.

• For sample size:
  – the sample must have more observations than variables.
  – the minimum absolute sample size should be 50 observations.

• Maximize the number of observations per variable, with a minimum of five and hopefully at least ten observations per variable.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Stage 3: Assumptions in Factor Analysis

• Three Basic Decisions
  2. Design of study in terms of number of variables, measurement properties of variables, and the type of variables.
  3. Sample size required.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Assumptions

• Multicollinearity
  – Assessed using MSA (measure of sampling adequacy).
    • The MSA is measured by the Kaiser-Meyer-Olkin (KMO) statistic. As a measure of sampling adequacy, the KMO predicts if data are likely to factor well based on correlation and partial correlation. KMO can be used to identify which variables to drop from the factor analysis because they lack multicollinearity.
    • There is a KMO statistic for each individual variable, and their sum is the KMO overall statistic. KMO varies from 0 to 1.0. Overall KMO should be .50 or higher to proceed with factor analysis. If it is not, remove the variable with the lowest individual KMO statistic value one at a time until KMO overall rises above .50, and each individual variable KMO is above .50.

• Homogeneity of sample factor solutions

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Rules of Thumb 3–2

Testing Assumptions of Factor Analysis

• There must be a strong conceptual foundation to support the assumption that a structure does exist before the factor analysis is performed.

• A statistically significant Bartlett’s test of sphericity (sig. < .05) indicates that sufficient correlations exist among the variables to proceed.

• Measure of Sampling Adequacy (MSA) values must exceed .50 for both the overall test and each individual variable. Variables with values less than .50 should be omitted from the factor analysis one at a time, with the smallest one being omitted each time.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Stage 4: Deriving Factors and Assessing Overall Fit

• Selecting the factor extraction method – common vs. component analysis.
• Determining the number of factors to represent the data.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Extraction Decisions

• Which method?
  – Principal Components Analysis
  – Common Factor Analysis

• How to rotate?
  – Orthogonal or Oblique rotation

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Extraction Method Determines the Types of Variance Carried into the Factor Matrix

Diagonal Value

Unity (1)

Communality

Variance

Total Variance

Common

Specific and Error

Variance extracted

Variance not used

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Principal Components vs. Common?

• Two Criteria
  – Objectives of the factor analysis.
  – Amount of prior knowledge about the variance in the variables.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Number of Factors?

- A Priori Criterion
- Latent Root Criterion
- Percentage of Variance
- Scree Test Criterion

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Eigenvalue Plot for Scree Test Criterion

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Rules of Thumb 3–3
Choosing Factor Models and Number of Factors

• Although both component and common factor analysis models yield similar results in common research settings (30 or more variables or communalities of .60 for most variables):
  – the component analysis model is most appropriate when data reduction is paramount.
  – the common factor model is best in well-specified theoretical applications.
• Any decision on the number of factors to be retained should be based on several considerations:
  – use of several stopping criteria to determine the initial number of factors to retain.
  – Factors With Eigenvalues greater than 1.0.
  – A pre-determined number of factors based on research objectives and/or prior research.
  – Enough factors to meet a specified percentage of variance explained, usually 60% or higher.
  – Factors shown by the scree test to have substantial amounts of common variance (i.e., factors before inflection point).
  – More factors when there is heterogeneity among sample subgroups.
• Consideration of several alternative solutions (one more and one less factor than the initial solution) to ensure the best structure is identified.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Processes of Factor Interpretation

• Estimate the Factor Matrix
• Factor Rotation
• Factor Interpretation
• Respecification of factor model, if needed, may involve . . .
  – Deletion of variables from analysis
  – Desire to use a different rotational approach
  – Need to extract a different number of factors
  – Desire to change method of extraction

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Rotation of Factors

• Factor rotation

  – the reference axes of the factors are turned about the origin until some other position has been reached. Since unrotated factor solutions extract factors based on how much variance they account for, with each subsequent factor accounting for less variance. The ultimate effect of rotating the factor matrix is to redistribute the variance from earlier factors to later ones to achieve a simpler, theoretically more meaningful factor pattern.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Two Rotational Approaches

1. Orthogonal
   – axes are maintained at 90 degrees.

2. Oblique
   – axes are not maintained at 90 degrees.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Orthogonal Factor Rotation

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Oblique Factor Rotation

Unrotated Factor II

Orthogonal Rotation: Factor II

Oblique Rotation: Factor II

V1

V2

Oblique Rotation: Factor I

Orthogonal Rotation: Factor I

V3

V4

V5

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Orthogonal Rotation Methods

• Quartimax (simplify rows)

• Varimax (simplify columns)

• Equimax (combination)

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Rules of Thumb 3–4
Choosing Factor Rotation Methods

• Orthogonal rotation methods
  – are the most widely used rotational methods.
  – are The preferred method when the research goal is data reduction to either a smaller number of variables or a set of uncorrelated measures for subsequent use in other multivariate techniques.

• Oblique rotation methods
  – best suited to the goal of obtaining several theoretically meaningful factors or constructs because, realistically, very few constructs in the “real world” are uncorrelated

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Which Factor Loadings Are Significant?

• Customary Criteria = Practical Significance.
• Sample Size & Statistical Significance.
• Number of Factors (↑ = >) and/or Variables (↑ = <).

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Guidelines for Identifying Significant Factor Loadings Based on Sample Size

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<td>.75</td>
<td>50</td>
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*Significance is based on a .05 significance level (a), a power level of 80 percent, and standard errors assumed to be twice those of conventional correlation coefficients.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Rules of Thumb 3–5

Assessing Factor Loadings

• While factor loadings of $+.30$ to $+.40$ are minimally acceptable, values greater than $+.50$ are considered necessary for practical significance.

• To be considered significant:
  – A smaller loading is needed given either a larger sample size, or a larger number of variables being analyzed.
  – A larger loading is needed given a factor solution with a larger number of factors, especially in evaluating the loadings on later factors.

• Statistical tests of significance for factor loadings are generally very conservative and should be considered only as starting points needed for including a variable for further consideration.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Stage 5: Interpreting the Factors

• Selecting the factor extraction method – common vs. component analysis.
• Determining the number of factors to represent the data.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Interpreting a Factor Matrix:

1. Examine the factor matrix of loadings.
2. Identify the highest loading across all factors for each variable.
3. Assess communalities of the variables.
4. Label the factors.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Rules of Thumb 3–6

Interpreting The Factors

• An optimal structure exists when all variables have high loadings only on a single factor.

• Variables that cross-load (load highly on two or more factors) are usually deleted unless theoretically justified or the objective is strictly data reduction.

• Variables should generally have communalities of greater than .50 to be retained in the analysis.

• Respecification of a factor analysis can include options such as:
  – deleting a variable(s),
  – changing rotation methods, and/or
  – increasing or decreasing the number of factors.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Stage 6: Validation of Factor Analysis

• Confirmatory Perspective.
• Assessing Factor Structure Stability.
• Detecting Influential Observations.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Stage 7: Additional Uses of Factor Analysis Results

- Selecting Surrogate Variables
- Creating Summated Scales
- Computing Factor Scores

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Rules of Thumb 3–7

Summated Scales

• A summated scale is only as good as the items used to represent the construct. While it may pass all empirical tests, it is useless without theoretical justification.

• Never create a summated scale without first assessing its unidimensionality with exploratory or confirmatory factor analysis.

• Once a scale is deemed unidimensional, its reliability score, as measured by Cronbach’s alpha:
  – should exceed a threshold of .70, although a .60 level can be used in exploratory research.
  – the threshold should be raised as the number of items increases, especially as the number of items approaches 10 or more.

• With reliability established, validity should be assessed in terms of:
  – convergent validity  =  scale correlates with other like scales.
  – discriminant validity  =  scale is sufficiently different from other related scales.
  – nomological validity  =  scale “predicts” as theoretically suggested.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Rules of Thumb 3–8

Representing Factor Analysis In Other Analyses

• The single surrogate variable:
  – Advantages: simple to administer and interpret.
  – Disadvantages:
    • does not represent all “facets” of a factor
    • prone to measurement error.

• Factor scores:
  – Advantages:
    • represents all variables loading on the factor,
    • best method for complete data reduction.
    • Are by default orthogonal and can avoid complications caused by multicollinearity.
  – Disadvantages:
    • interpretation more difficult since all variables contribute through loadings
    • Difficult to replicate across studies.
Rules of Thumb 3–8 (cont.)

Representing Factor Analysis In Other Analyses

• Summated scales:
  – Advantages:
    • compromise between the surrogate variable and factor score options.
    • reduces measurement error.
    • represents multiple facets of a concept.
    • easily replicated across studies.
  – Disadvantages:
    • includes only the variables that load highly on the factor and excludes those having little or marginal impact.
    • not necessarily orthogonal.
    • Require extensive analysis of reliability and validity issues.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
### Description of HBAT Primary Database Variables

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<th>Variable Description</th>
<th>Variable Type</th>
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<td>X3 Firm Size</td>
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<tr>
<td>X4 Region</td>
<td>nonmetric</td>
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<tr>
<td>X5 Distribution System</td>
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<tr>
<td><strong>Performance Perceptions Variables</strong></td>
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<tr>
<td>X6 Product Quality</td>
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<tr>
<td>X7 E-Commerce Activities/Website</td>
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<tr>
<td>X8 Technical Support</td>
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<tr>
<td>X9 Complaint Resolution</td>
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<tr>
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</tr>
<tr>
<td>X14 Warranty &amp; Claims</td>
<td>metric</td>
</tr>
<tr>
<td>X15 New Products</td>
<td>metric</td>
</tr>
<tr>
<td>X16 Ordering &amp; Billing</td>
<td>metric</td>
</tr>
<tr>
<td>X17 Price Flexibility</td>
<td>metric</td>
</tr>
<tr>
<td>X18 Delivery Speed</td>
<td>metric</td>
</tr>
<tr>
<td><strong>Outcome/Relationship Measures</strong></td>
<td></td>
</tr>
<tr>
<td>X19 Satisfaction</td>
<td>metric</td>
</tr>
<tr>
<td>X20 Likelihood of Recommendation</td>
<td>metric</td>
</tr>
<tr>
<td>X21 Likelihood of Future Purchase</td>
<td>metric</td>
</tr>
<tr>
<td>X22 Current Purchase/Usage Level</td>
<td>metric</td>
</tr>
<tr>
<td>X23 Consider Strategic Alliance/Partnership in Future</td>
<td>nonmetric</td>
</tr>
</tbody>
</table>

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
## Rotated Component Matrix

**“Reduced Set” of HBAT Perceptions Variables**

<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Communality</th>
</tr>
</thead>
<tbody>
<tr>
<td>X9 – Complaint Resolution</td>
<td>.933</td>
<td>1.0</td>
<td>.890</td>
<td>1.0</td>
<td>.890</td>
</tr>
<tr>
<td>X18 – Delivery Speed</td>
<td>.931</td>
<td>.894</td>
<td>1.0</td>
<td>.894</td>
<td>1.0</td>
</tr>
<tr>
<td>X16 – Order &amp; Billing</td>
<td>.886</td>
<td>.806</td>
<td>.860</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>X12 – Salesforce Image</td>
<td>.898</td>
<td>.860</td>
<td>.780</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>X7  – E-Commerce Activities</td>
<td>.868</td>
<td>.780</td>
<td>.743</td>
<td>.585</td>
<td>1.0</td>
</tr>
<tr>
<td>X10 – Advertising</td>
<td>.743</td>
<td>.940</td>
<td>.933</td>
<td>.891</td>
<td>1.0</td>
</tr>
<tr>
<td>X8  – Technical Support</td>
<td></td>
<td>.940</td>
<td>.933</td>
<td>.891</td>
<td>1.0</td>
</tr>
<tr>
<td>X14 – Warranty &amp; Claims</td>
<td></td>
<td></td>
<td>.892</td>
<td>.798</td>
<td>1.0</td>
</tr>
<tr>
<td>X6  – Product Quality</td>
<td></td>
<td></td>
<td>-.730</td>
<td>.661</td>
<td>1.0</td>
</tr>
</tbody>
</table>

| Sum of Squares             | 2.589     | 2.216     | 1.846     | 1.406     | 8.057       |
| Percentage of Trace        | 25.893    | 22.161    | 18.457    | 14.061    | 80.572      |

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Scree Test for HBAT Component Analysis

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Summary

1. What are the major uses of factor analysis?
2. What is the difference between component analysis and common factor analysis?
3. Is rotation of factors necessary?
4. How do you decide how many factors to extract?
5. What is a significant factor loading?
6. How and why do you name a factor?
7. Should you use factor scores or summated ratings in follow-up analyses?

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
蕭文龍，
多變量分析最佳入門實用書--SPSS+LISREL, 第二版, 基峰資訊, 2009
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本書可作為Hair（2006）Multivariate Data Analysis一書的最佳輔助參考書籍。

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• Ch21 研究流程、論文結構與研究範例
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• 附錄B ENDNOTE書目管理軟體使用說明
• 附錄C 軟體的取得與說明LISREL

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