Social Media Marketing Analytics
社群網路行銷分析

探索性因素分析
(Exploratory Factor Analysis)

1032SMMA06
TLMXJ1A (MIS EMBA)
Fri 12,13,14 (19:20-22:10) D326

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2015-04-24
<table>
<thead>
<tr>
<th>週次 (Week)</th>
<th>日期 (Date)</th>
<th>內容 (Subject/Topics)</th>
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<td>2015/03/13</td>
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週次 (Week)  日期 (Date)  內容 (Subject/Topics)
10  2015/05/01  期中報告 (Midterm Presentation)
11  2015/05/08  確認性因素分析 (Confirmatory Factor Analysis)
12  2015/05/15  社會網路分析 (Social Network Analysis)
13  2015/05/22  社群網路行銷個案分析 II
             (Case Study on Social Media Marketing II)
14  2015/05/29  社群運算與大數據分析
             (Social Computing and Big Data Analytics)
15  2015/06/05  社群網路情感分析 (Sentiment Analysis on Social Media)
16  2015/06/12  期末報告 I (Term Project Presentation I)
17  2015/06/19  端午節補假 (放假一天)
18  2015/06/26  期末報告 II (Term Project Presentation II)
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

(Hair et al., 2009)
Chapter 3
Exploratory Factor Analysis

(Hair et al., 2009)
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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<tr>
<th></th>
<th>$V_1$</th>
<th>$V_2$</th>
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<td>.428</td>
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<td>.326</td>
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<td>.466</td>
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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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<thead>
<tr>
<th></th>
<th>V₃</th>
<th>V₈</th>
<th>V₉</th>
<th>V₂</th>
<th>V₆</th>
<th>V₇</th>
<th>V₄</th>
<th>V₁</th>
<th>V₅</th>
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<td></td>
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<td>V₈ In-store Service</td>
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<td>.774</td>
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<td>.325</td>
<td>.378</td>
<td>.472</td>
<td>.765</td>
<td>1.00</td>
</tr>
</tbody>
</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

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
1. Objectives of Factor Analysis
2. Designing a Factor Analysis
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6. Validation of Factor Analysis
7. Additional uses of Factor Analysis Results

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

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

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Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
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
Rules of Thumb 3–1

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
5 Variables : 1 Factor

(5:1)

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Customer Perceived Value, Customer Satisfaction, and Loyalty

5 Variables : 1 Factor

(5:1)

Variable 1
Variable 2
Variable 3
Variable 4
Variable 5

Loyalty

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

5 Variables (Items) (5:1)

(Zeithaml, Berry & Parasuraman, 1996)

- Say positive things about XYZ to other people.
- Recommend XYZ to someone who seeks your advice.
- Encourage friends and relatives to do business with XYZ.
- Consider XYZ your **first choice** to buy services.
- Do more business with XYZ in the next few years.

minimum absolute sample size should be 50 observations

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Sample Size: at least ten observations per variable (1:10)

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall
Sample Size:
25 variables * 10 observations
(25 * 10 = 250)

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

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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
Factor Analysis Decision Process

1. Objectives of Factor Analysis
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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

<table>
<thead>
<tr>
<th>Diagonal Value</th>
<th>Variance</th>
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<td>Unity (1)</td>
<td>Total Variance</td>
</tr>
<tr>
<td></td>
<td>Common</td>
</tr>
<tr>
<td></td>
<td>Specific and Error</td>
</tr>
</tbody>
</table>

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

FIGURE 3-6 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

Unrotated Factor I

Orthogonal Rotation: Factor I

Oblique Rotation: Factor I

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

<table>
<thead>
<tr>
<th>Factor Loading</th>
<th>Sample Size Needed for Significance*</th>
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<td>.75</td>
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</table>

*Significance is based on a .05 significance level (α), 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
Factor Analysis Decision Process

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

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
Factor Analysis Decision Process

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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
Factor Analysis Decision Process

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

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.

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

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Variable Type</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Data Warehouse Classification Variables</strong></td>
<td></td>
</tr>
<tr>
<td>X1 Customer Type</td>
<td>nonmetric</td>
</tr>
<tr>
<td>X2 Industry Type</td>
<td>nonmetric</td>
</tr>
<tr>
<td>X3 Firm Size</td>
<td>nonmetric</td>
</tr>
<tr>
<td>X4 Region</td>
<td>nonmetric</td>
</tr>
<tr>
<td>X5 Distribution System</td>
<td>nonmetric</td>
</tr>
<tr>
<td><strong>Performance Perceptions Variables</strong></td>
<td></td>
</tr>
<tr>
<td>X6 Product Quality</td>
<td>metric</td>
</tr>
<tr>
<td>X7 E-Commerce Activities/Website</td>
<td>metric</td>
</tr>
<tr>
<td>X8 Technical Support</td>
<td>metric</td>
</tr>
<tr>
<td>X9 Complaint Resolution</td>
<td>metric</td>
</tr>
<tr>
<td>X10 Advertising</td>
<td>metric</td>
</tr>
<tr>
<td>X11 Product Line</td>
<td>metric</td>
</tr>
<tr>
<td>X12 Salesforce Image</td>
<td>metric</td>
</tr>
<tr>
<td>X13 Competitive Pricing</td>
<td>metric</td>
</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>Variable</th>
<th>Component 1</th>
<th>Component 2</th>
<th>Component 3</th>
<th>Component 4</th>
<th>Communality</th>
</tr>
</thead>
<tbody>
<tr>
<td>X9 – Complaint Resolution</td>
<td>.933</td>
<td></td>
<td></td>
<td></td>
<td>.890</td>
</tr>
<tr>
<td>X18 – Delivery Speed</td>
<td>.931</td>
<td></td>
<td></td>
<td></td>
<td>.894</td>
</tr>
<tr>
<td>X16 – Order &amp; Billing</td>
<td>.886</td>
<td></td>
<td></td>
<td></td>
<td>.806</td>
</tr>
<tr>
<td>X12 – Salesforce Image</td>
<td></td>
<td>.898</td>
<td></td>
<td></td>
<td>.860</td>
</tr>
<tr>
<td>X7 – E-Commerce Activities</td>
<td>.868</td>
<td></td>
<td></td>
<td></td>
<td>.780</td>
</tr>
<tr>
<td>X10 – Advertising</td>
<td></td>
<td>.743</td>
<td></td>
<td></td>
<td>.585</td>
</tr>
<tr>
<td>X8 – Technical Support</td>
<td></td>
<td></td>
<td>.940</td>
<td></td>
<td>.894</td>
</tr>
<tr>
<td>X14 – Warranty &amp; Claims</td>
<td></td>
<td></td>
<td>.933</td>
<td></td>
<td>.891</td>
</tr>
<tr>
<td>X6 – Product Quality</td>
<td></td>
<td></td>
<td></td>
<td>.892</td>
<td>.798</td>
</tr>
<tr>
<td>X13 – Competitive Pricing</td>
<td></td>
<td></td>
<td></td>
<td>-.730</td>
<td>.661</td>
</tr>
</tbody>
</table>

**Sum of Squares**

<table>
<thead>
<tr>
<th>Component</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.589</td>
</tr>
<tr>
<td>2</td>
<td>2.216</td>
</tr>
<tr>
<td>3</td>
<td>1.846</td>
</tr>
<tr>
<td>4</td>
<td>1.406</td>
</tr>
</tbody>
</table>

**Percentage of Trace**

<table>
<thead>
<tr>
<th>Component</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25.893</td>
</tr>
<tr>
<td>2</td>
<td>22.161</td>
</tr>
<tr>
<td>3</td>
<td>18.457</td>
</tr>
<tr>
<td>4</td>
<td>14.061</td>
</tr>
</tbody>
</table>

**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，
統計分析入門與應用：SPSS中文版＋PLS-SEM (SmartPLS)，碁峰資訊, 2014

Source: http://24h.pchome.com.tw/books/prod/DJAV0S-A82328045
蕭文龍
統計分析入門與應用：SPSS中文版＋PLS-SEM（SmartPLS），碁峰資訊，2014
蕭文龍,
統計分析入門與應用：SPSS中文版＋PLS-SEM (SmartPLS),
碁峰資訊, 2014

- 國內第一本全面介紹 SmartPLS 操作、PLS-SEM 結構方程模式的實用書
- 國內第一本深入探討最新量表發展、中介和調節變數的應用、Reflective (反映性) 和 Formative (形成性) 指標的發展和模式的指定
- 本書適合作為統計分析和多變量分析的教科書，也是 Hair, Black, Babin, and Anderson 所撰寫的 Multivariate data analysis Multivariate Data Analysis 多變量分析的最佳輔助參考書籍，更是 Hair, Hult, Ringle, and Sarstedt 所撰寫的 A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) 的最優輔助參考書籍。

Source: http://24h.pchome.com.tw/books/prod/DJAV0S-A82328045
蕭文龍,
統計分析入門與應用：SPSS中文版＋PLS-SEM (SmartPLS),
碁峰資訊, 2014

• 以實用的角度引導學員從學習社會科學概念開始介紹，
  到完成一份專題、研究生論文和論文投稿，對於大學部
  專題，碩博士學生，量化的研究人員都有莫大的幫助。

• 以統計分析(多變量分析)為主軸，整合了理論的介紹、量
  化的研究、量表的發展、卡方檢定、因素分析、迴歸分
  析、區別分析和邏輯迴歸、單因子變異數分析、多變量
  變異數分析、典型相關分析、信度和效度分析、聯合分
  析多元尺度和集群分析，第二代統計技術—結構方程模式
  (SEM)。

• 內容涵蓋SmartPLS基本操作、PLS-SEM結構方程模式的學
  習範例、反映性和形成性指標與模式的指定、二階和高
  階因果關係、SEM結構方程模式實例、中介和調節變數
  的應用、論文結構與研究範例和EndNote書目管理軟體使
  用說明。

Source: http://24h.pchome.com.tw/books/prod/DJAV0S-A82328045
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• chapter 01 統計分析簡介與數量方法的基礎
• chapter 02 SPSS 的基本操作
• chapter 03 量表的發展，信度和效度
• chapter 04 檢視資料與敘述性統計
• chapter 05 統相關分析(Correlation Analysis)
• chapter 06 卡方檢定
• chapter 07 平均數比較(t 檢定)
• chapter 08 因素分析
• chapter 09 迴歸分析
• chapter 10 區別分析與邏輯迴歸

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• chapter 12 多變量變異數分析
• chapter 13 典型相關
• chapter 14 聯合分析、多元尺度方法和集群分析
• chapter 15 結構方程模式之 Partial Least Squares (PLS) 偏最小平方
• chapter 16 Smartplls 統計分析軟體介紹
• chapter 17 PLS-SEM(SmartPLS) 結構方程模式的學習範例
• chapter 18 PLS-SEM 結構方程模式實例
• chapter 19 反映性 Reflective 與形成性 Formative 模式
• chapter 20 交互作用、中介和調節 (干擾)
• chapter 21 研究流程、論文結構與發表於期刊的建議

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多變量分析最佳入門實用書--SPSS+LISREL, 第二版,
碁峰資訊, 2009

多變量分析最佳入門實用書--SPSS+LISREL(第二版)(平裝)

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作者：蕭文龍
ISBN：9789861817347
出版社：碁峰資訊
出版日期：2009/06/09

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・本書通過Scientific Software International (SSI) LISREL原廠審核通過，成為LISREL原廠推薦的第四本華文書，相關網址：http://www.ssicentral.com/cn/books.html#sem

・本書可作為Hair（2006）Multivariate Data Analysis一書的最佳輔助參考書籍

・從實用的角度出發，完整介紹社會科學概念、統計軟體的運用以及統計分析，協助學習者完成量化的研究及其相關專題或論文。

・內容整合了社會科學概念、量化研究、量表發展與統計分析。

・文中納入第二代統計技術，包括結構方程模式(SEM)、LISREL基本操作SEM結構方程模式範例與SEM結構方程模式實例。

・特別介紹研究流程、論文結構與研究範例、EndNote書目管理軟體使用說明、LISREL和Nvivo軟體的取得與說明。

・隨書光碟附贈LISREL For Windows學生版

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• Ch11 多變量變異數分析
• Ch12 典型相關

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- Ch14 SEM結構方程模式
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- Ch17 結構方程模式的學習範例進階
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- 附錄C 軟體的取得與說明LISREL

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