Social Media Marketing Management

探索性因素分析
(Exploratory Factor Analysis)

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Min-Yuh Day
戴敏育
Assistant Professor

Dept. of Information Management, Tamkang University

http://mail.tku.edu.tw/myday/
2013-05-28
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<th>內容（Subject/Topics）</th>
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<td>1</td>
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<td>社會媒體行銷管理課程介紹 (Course Orientation of Social Media Marketing Management)</td>
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<td>社群網路 (Social Media: Facebook, Youtube, Blog, Microblog)</td>
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<td>行銷管理論文研討 (Paper Reading on Marketing Management)</td>
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<td>期中報告 (Midterm Presentation)</td>
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<td>15</td>
<td>102/05/28</td>
<td>探索性因素分析 (Exploratory Factor Analysis)</td>
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<td>102/06/04 (&gt; 6/01)</td>
<td>確認性因素分析 (Confirmatory Factor Analysis)</td>
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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
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
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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<tr>
<th></th>
<th>$V_1$</th>
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<th>$V_3$</th>
<th>$V_4$</th>
<th>$V_5$</th>
<th>$V_6$</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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<th>V_3 Return Policy</th>
<th>V_8 In-store Service</th>
<th>V_9 Store Atmosphere</th>
<th>V_2 Store Personnel</th>
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<tr>
<td>V_8 In-store Service</td>
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<tr>
<td>V_9 Store Atmosphere</td>
<td>0.774</td>
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<td>1.00</td>
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<td>V_6 Assortment Depth</td>
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<tr>
<td>V_7 Assortment Width</td>
<td>0.471</td>
<td>0.435</td>
<td>0.468</td>
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<td>0.427</td>
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<td>V_1 Price Level</td>
<td>0.302</td>
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<td>0.372</td>
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<td>0.281</td>
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<tr>
<td>V_5 Product Quality</td>
<td>0.307</td>
<td>0.240</td>
<td>0.326</td>
<td>0.406</td>
<td>0.325</td>
<td>0.378</td>
<td>0.472</td>
<td>0.765</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

Factors

- Service Quality
- Food Quality

Variables

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

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
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
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
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

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

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

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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<tr>
<td>.35</td>
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<td>60</td>
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<tr>
<td>.75</td>
<td>50</td>
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</table>

*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.

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

<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>
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</tr>
<tr>
<td>X3 Firm Size</td>
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</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>
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</thead>
<tbody>
<tr>
<td>X9 – Complaint Resolution</td>
<td>.933</td>
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<td></td>
<td></td>
<td>.890</td>
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<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>
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<td></td>
<td></td>
<td>.806</td>
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<tr>
<td>X12 – Salesforce Image</td>
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<td>.898</td>
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<td></td>
<td>.860</td>
</tr>
<tr>
<td>X7 – E-Commerce Activities</td>
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<td></td>
<td>.868</td>
<td></td>
<td>.780</td>
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<tr>
<td>X10 – Advertising</td>
<td></td>
<td></td>
<td>.743</td>
<td></td>
<td>.585</td>
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<tr>
<td>X8 – Technical Support</td>
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<td></td>
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<td>.940</td>
<td>.894</td>
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<tr>
<td>X14 – Warranty &amp; Claims</td>
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<td></td>
<td>.933</td>
<td></td>
<td>.891</td>
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<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: 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,
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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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- Ch01 社會科學的研究與數量方法的基礎
- Ch02 SPSS的基本操作
- Ch03 檢視資料與敘述性統計
- Ch04 相關分析
- Ch05 卡方檢定
- Ch06 平均數比較
- Ch07 因素分析
- Ch08 迴歸分析
- Ch09 區別分析與邏輯迴歸
- Ch10 單變量變異數分析
- 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
- Ch15 LISREL的基本操作
- Ch16 結構方程模式的學習範例
- Ch17 結構方程模式的學習範例進階
- Ch18 SEM結構方程模式實例
- Ch19 聯合分析、多元尺度方法和集群分析
- Ch20 交互作用、中介和調節(干擾)效果之驗證
- Ch21 研究流程、論文結構與研究範例
- 附錄A 統計分配表
- 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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