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ΤΜΗΜΑ ΔΙΟΙΚΗΣΗΣ ΕΠΙΧΕΙΡΗΣΕΩΝ
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Research Instrument Validation

By

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Instrument Validation

To ensure the appropriateness of the research instrument it will be tested for:

1. **Normality**
2. **Content Validity**
3. **Construct Validity and**
4. **Reliability**

1. **Normality:** The most common assumption in multivariate statistical techniques is the normality that means that a variable is normally distributed.

West et al. (1995) suggested to testing for univariate normality, all items, interpreting the absolute value of the skewness and kurtosis indices. They considered scores to be moderately non-normal if they demonstrated skewness index values ranking from 2 to 3 and kurtosis ranking from 7 to 21. Extreme non-normality is defined by skewness index values greater than 3 and kurtosis values great than 21. As a result the items are normally distributed and hence are acceptable for further analysis if skewness and kurtosis values are below to 2 and 7 respectively. **Kline (1998)** suggests that skewness greater than 3.0 and kurtosis greater than 10.0 may suggest a problem with the data. Multivariate non-normality can usually be identified through univariate procedures **(Kline, 1998)**.

Jarque and Bera (1987) suggested the next formula: $\boldsymbol{N}\left[\frac{\boldsymbol{S_K^2}}{\mathbf{6}}+\frac{(\boldsymbol{\beta}-\mathbf{3})^2}{\mathbf{24}}\right]$ ~ X^2 with 2 d.f. If the value of calculated Jarque-Bera is higher than the critical value of X^2 in a specific significance level, then the hypothesis of normality is rejected.

According Hair et al. (1995) the normality test can be done by the comparison of $\boldsymbol{z\ value}=\frac{\boldsymbol{S_K}}{\sqrt{\frac{\mathbf{6}}{\boldsymbol{N}}}}$ with a critical z-value in a specific significance level. If the value of calculated z exceeds the critical value, then the distribution is non- normal.

2. **Content Validity:** The most basic type of validity is the face or content validity **(Zikmund, 1997)**, i.e., agreement among professionals that the scale is measuring it is supposed to measure **(Chu and Murramann, 2006)**. To ensure content validity **Kim et al. (2008)** suggest: (a) a review of the literature on the subject of the study, (b) a pilot test

in a panel of experts (professors and professionals), (c) a sample of respondents separate from those included in the pilot test to check the questionnaire. These and all pilot test respondents excluded from the main sample. Many times measures are constructed by adopting constructs validated by other researches.

3. Construct Validity: Construct validity attempts to identify the underlying constructs being measured and determine how well the test represents them **(Cooper and Schindler, 1998)**. There are three ways in which construct validity is assessed **(Cao and Dowlatshahi, 2005):**

(a) A test of unidimentionality: Unidimentionality provides evidence of a single latent construct **(Flynn, 1990)**. There are two common methods to assessing the unidimentionality of a measure: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

The general purpose of **Exploratory Factor Analysis** is to find a way of summarizing the information contained in a number of original variables into smaller set of new, composite dimensions or factors with the minimum loss of information **(Hair et al., 1995)**. In the EFA the structure of the factor model or the underlying theory is not known or specified a priori. Rather, data are used to help reveal or identify the structure of the factor model. Thus, EFA can be viewed as a technique to aid in theory building.

In **Confirmatory Factor Analysis** the precise structure of the factor model, which is based on some underlying theory is hypothesized **(Sharma, 1996).**

(b) A test of convergent validity: Convergent validity relates to the degree to which multiple methods of measuring a variable provide the same results **(Spector, 1992; Churchill, 1979)**. Convergent validity is considered acceptable when all item loadings are greater than 0,5 **(Wixom and Watson, 2001)** and the items for all construct load onto only one factor with an eigenvalue greater than 1 **(Kim et al., 2008). Chin (1988)** suggested that convergent validity can be tested by assessing the composite reliability and the variance extracted. Although many studies use 0,5 as an indication of reliability of measures, a score of 0,7 is the recommended value for reliability. For variance extracted by measures, a score of 0,5 indicates acceptability **(Fornell and Lacker (1981).**

(c) A test of discriminant validity: Discriminant validity deals with the concept that dissimilar constructs should be different **(Burns and Bush, 1995)**. In order to demonstrate that the constructs are distinct we must create a matrix containing the correlation coefficients among the constructs and in the diagonal of the matrix the Cronbach's alpha coefficients. The correlation coefficients within a column should be less than the coefficient alpha found in the diagonal **(Churchill, 1979)**. This would indicate that there is higher correlation within the variables than between the variables, using the same methods **(Widener, 2004)**. Discriminant validity can be checked also by examining whether the correlations between the variables are lower than the square root of the average variance extracted **(Kim et al., 2008)**. **Fornell and Lacker (1981)** suggest assessing Discriminant validity by examining the correlations among questions. The role of thumb in Discriminant validity is that a measure should correlate with all measures of the same construct more highly than it does with any measure of other constructs **(Chin, 1988).**

4. Reliability: Reliability is one of the major criteria for evaluating research instruments **(Chu and Murramann, 2006).** The assessment of the model includes the estimation of reliability which measures the internal consistency. Internal consistency will be calculated using Cronbach's alpha coefficient and Formell's composite reliability **(Fornell and Larcker, 1981)** and is based on the correlations among the items that constitute a measure. The value of Cronbach's alpha coefficient should be higher than the minimum cutoff score of 0,60 **(Nunally, 1978)** or 0,65 **(Lee and Kim, 1999)** or 0,70 **(Nunally, 1978; Nunally and Bernstein, 1994)**. Although the Cronbach's alpha indicator is the most frequent test to assess reliability, some authors consider that it underestimates reliability **(Smith, 1974)**. Consequently, the use of composite reliability has been suggested **(Joreskog, 1971)**, considering a cut-off value of 0.6 **(Nunnally & Bernstein, 1994)**. According to **Fornell and Larcker (1981),** composite reliability should be greater than the benchmark of 0,7 to be considered adequate.

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