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Structural Approach for Organizational Agility Path Analysis

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Abstract. The aim of this study is to introduce a structural approach to increase the agility of an organization. A conceptual model for performing a Path analysis is being suggested. A methodological approach using Path Analysis and Structural Equation Modeling is being proposed.

INTRODUCTION

The business environment is rapidly changing and one of the main yearly goals in most companies is to be more agile. The capability to adopt these changes is based on the organizational agility. Depending on the way the tools and methodologies applied will determine how fast the organization can adopt. Companies that are adopting fast to agile methodologies are being more productive and competitive compared to their opponents. Most managerial figures are considering organizational agility as critical for the business success and profitable growth [1].

To determine if the applied approach is correct most companies conduct a survey in order to make an analysis of the gathered data. The analysist creates questionnaires which gather information related to the subject of interest for the future analysis. Structural Equation Modeling (SEM) is a statistical modeling visual technique that is frequently used to analyze and visualize the gathered data from the survey results [2]. In this study we are going to present how using SEM's path analysis will help us to determine the organizational agility of a company.

Structural Equation Modeling (SEM) Concept

A combination of regression, discriminant, path and factor analysis provides a convenient framework that can be combined in statistical model called Structural Equation Modeling (SEM). SEM is a statistical tool that contains the majority of all common multivariate procedures [2]. When SEM is used the data typically is being graphically visualized via Path Diagrams.

SEM uses models to depict relationships among observed variables gained from the obtained survey. The goal of utilizing structural modelling is to offer a quantifiable examination of a theoretical model which is assumed by the scientist. The models define the relationship between the variables and their constructs. Variables can be defined as dependent or independent whether the gained data is observed or latent [3].

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Structural Equation Modelling Advantages

Statistical methods are not capable of dealing with sophisticated theories and utilize a limited number of variables. This however is limiting and does not give the option to solve complex phenomena. In sophisticated theoretical models using simple bivariate correlation will not be efficient enough. SEM allows complex phenomena to be statistically modeled and because of the quantitative fashion techniques it offers, is becoming a more commonly used method for theoretical models confirmation or disconfirmation. The more reliable and valid the obtained from the measurement instruments scores are with the greater recognition of the method is being provided. SEM techniques are focusing on measurement error unlike other methods when measurement error is statistical data analysis are being approached as separate threads. Alongside measurement errors terms, latent and observed variable terms are being in certain SEM models.

By using SEM's multiple-group models we can obtain the key differences in group theoretical models and collect data at more than one level while analyzing educational data. The main and interaction effects of SEM models can be tested by using interaction terms. The basic statistical methods are getting less incapable of analyzing complex phenomena compared to the capabilities of the advanced SEM models. SEM software programs are based on Windows software packages meaning that they don't require advanced statistical training courses and workshops with the intention of avoid failing to properly analyze sophisticated theoretical models [3]

Factor Analysis

According to [5] exploratory factor analysis is an instrument used to recognize the relations between the respondent and the variable by reducing the data to smaller sets and exploring the underlying theoretical structure of the phenomena. The following methods are being used to perform an exploratory factor analysis:

- ✓ R-type factor analysis: A correlation matrix is used to calculate the factors in R-type factor analyses.
- ✓ Q-type factor analysis: By using an individual respondent the factors are being calculated in Q-type factor analysis.

The methods for driving factor are:

- ✓ Principle component factor analysis method: The method is being used to enlighten the maximum portion of variance of the original variable by using a minimum number of driving factors.
- ✓ Common factor analysis: The method is being used while the nature of the factors and the common error variance are not being specifically defined.

The following procedures needs to be performed in order to obtain the extracted factors:

1. Definition of the number of extracted factors.
2. Determination of the number of factors using Eigenvalue criteria. This is the most commonly used factor determination method.
3. Determine and select the factors from the plot graphs by using Eigenvalue criteria method in combination of exploratory data analysis with Scree test criteria method.

Orthogonal rotation: All the factors are uncorrelated, since the axes are maintained at 90 degrees. The following methods based on rotation are available in orthogonal rotation:

- ✓ QUARTIMAX: The variable is being loaded on a single factor by simplifying the rows.
- ✓ VARIMAX: Utilized to simplify the column of the factor matrix, thus the factor extracts are obviously related and there must be some isolation among the variables.
- ✓ EQUIMAX: Rows and columns are being simplified at the same time by using both QUARTIMAX and VARIMAX methods.

The researcher can regulate the significance level and the statistical power that needs to be used.

The statistical power and significance level can be regulated by the researcher. But there are some assumptions to have in mind as follows:

- ✓ Variables are metric. Dummy variables can be used in exceptional cases.
- ✓ The sample size should be higher than 200 and might be considered for 5 observations per variable.
- ✓ The homogeneity between the variable is being checked by Reliability analysis. The size of the samples and the number of variables are depended on their homogeneity.
- ✓ Multivariate normality is not a requirement while conducting exploratory factor analysis.
- ✓ The required correlation between the variables should be above 0.30.
- ✓ Outliers are forbidden in the data.

The Structural Equation Model

The Structural Equation Model is a tool used to represent the correlation between latent variables and indicators [7]. SEM can be articulated as:

$$y_i = \wedge_x \xi_i + \delta_i \quad (1)$$

$$x_i = \wedge_y \eta_i + \epsilon_i \quad (2)$$

The first model (1) is representing the exogenous latent variables:

y_i - variable vector

ξ_i - latent exogenous variables

δ - measurement error

Λ_x - matrix of the factor concerning indicators to the latent exogenous variable ξ_i

q - number of indicators of latent exogenous variables

Therefore, the matrix form of the model (1) should look like:

$$\begin{pmatrix} y_{i1} \\ \vdots \\ y_{iq} \end{pmatrix}_{q\times 1} = \begin{pmatrix} \lambda_{11} & \cdots & \lambda_{1n} \\ \vdots & \vdots & \vdots \\ \lambda_{q1} & \cdots & \lambda_{qn} \end{pmatrix}_{q\times n} \begin{pmatrix} \xi_{i1} \\ \vdots \\ \xi_{in} \end{pmatrix} + \begin{pmatrix} \delta_{i1} \\ \vdots \\ \delta_{iq} \end{pmatrix}_{q\times 1} \quad (3)$$

Model (2) is used for endogenous latent variables:

x_i - variables indicator in subject i latent endogenous variables

η_i -endogenous variables

p -number of indicators of latent endogenous variables

Λ_y - matrix of factor loadings

ϵ_i - errors

So, the matrix form of model (2) should look like:

$$\begin{pmatrix} \mathrm{x}_{\mathrm{i1}} \\ \vdots \\ \mathrm{x}_{\mathrm{ip}} \end{pmatrix}_{\mathrm{p\times 1}} = \begin{pmatrix} \lambda_{11} & \cdots & \lambda_{\mathrm{1m}} \\ \vdots & \vdots & \vdots \\ \lambda_{\mathrm{p1}} & \cdots & \lambda_{\mathrm{pm}} \end{pmatrix}_{\mathrm{p\times m}} \begin{pmatrix} \xi_{\mathrm{i1}} \\ \vdots \\ \xi_{\mathrm{im}} \end{pmatrix} + \begin{pmatrix} \delta_{\mathrm{i1}} \\ \vdots \\ \delta_{\mathrm{ip}} \end{pmatrix}_{\mathrm{p\times 1}} \quad (4)$$

Assessment of the Model

Model Assessment determines if the proposed model is suitable for the provided data. This is mostly observed through the goodness-of-fit indexes. In SEM χ^2 and χ^2/ν Ratio are the most frequently used indexes. The χ^2 chi-square test statistic value is dependent upon the sample size. It is an absolute fit index which assumes multivariate normality. The degrees of freedom of the model is ν.
Thus, the following indexes should be considered:

Root Mean Square Error of Approximation (RMSEA) Index

RMSEA value ranges between 0 and zero with preferable values for well-established model between 0.05 and 0.08.It is used to indicate the absolute/empirical fit [8]. Its statistics can be stated as:

$$\mathrm{RMSEA} = \left[\frac{(\chi^2\text{-}\nu)}{\nu(\mathrm{n\text{-}1})}\right]^{0.5}; \text{ with } \chi^2 = (\mathrm{n\text{-}1})\mathrm{Fmin}, \quad (5)$$

where, F_{min} is the minimum value of fit function.

Standardized Root Mean Square Residual (SRMR) Index

SKMR has a purpose of indicating the fit of the model of higher values. A good fit to the model is considered value which are less than 0.08 [10]. Its statistic can be stated as:

$$\mathrm{SRMR} = \left[\frac{\sum_{i=1}^{p}\sum_{j=1}^{i}\left[(s_{ij}\text{-}\hat{\sigma}_{ij})/(s_{ii.}s_{jj})\right]^2}{k(k+1)/2}\right]^{0.5}, \qquad (6)$$

where :

- $k = p+q$, s_{ij} -sample covariance's between observed variables
- σ_{ij} - expected components of variance-covariance matrix of the error vector of the model.

Comparative Fit Index (CFI)

A good indicator for the CFI model must be at least 0.90 or beyond to confirm that the model is appropriately definite[8]. The procedure used to compute CFI is stated as:

$$\mathrm{CFI} = 1\text{-}\frac{\mathrm{Max}\left((\chi^2_{\mathrm{model}}\text{-}\nu_{\mathrm{model}}),0\right)}{\mathrm{Max}\left((\chi^2_{\mathrm{null}}\text{-}\nu_{\mathrm{null}}),0\right)}, \qquad (7)$$

Tucker-Lewis Index (TLI)

A good indicator for the TLI model must be with value of at least 0.95 [8]. The procedure in which this index is computed can be stated as:

$$\mathrm{TLI} = \frac{(\chi^2_{\mathrm{null}}/\nu_{\mathrm{null}})\text{-}(\chi^2_{\mathrm{model}}/\nu_{\mathrm{model}})}{(\chi^2_{\mathrm{null}}/\nu_{\mathrm{null}})\text{-}1}, \qquad (8)$$

where $\chi^2_{\mathrm{null}}/\nu_{\mathrm{null}}$ is the ratio of chi-square to its degrees of freedom.

Path Analysis Model

The interpretation of effects can by developed by a method used for decomposing correlations into different pieces called path analysis. This method offers series of theoretical propositions which are commonly related to the cause and effect without manipulating the variables and in special cases can use multiple regression [6]. This is considered a supposal of the model and not a direct effect, meaning that it is simply a consequence of the technique. A common mistake made by the majority of people that use SEM techniques is to assume that the variables are causally related and leading them to think that the assumed propositions are supported. Most of the things that are being displayed in the path analysis are customizable. The cause to effect is being referred with a single pointed arrow. There are no casual relations assumed when a double headed curved arrow is used.

The dependent variables ***Y*** are endogenous and the independent variables ***X*** are exogenous. The path coefficient specifies the direct effect of a variable supposed to be a cause on another variable supposed to be an effect. Standardized due to the estimated correlations are the path coefficients unlike the path regression coefficient which is unstandardized. Two subscripts are being used to indicate the Path coefficients: path from 1 to 2 in the exemplar path model in fig.1 is written p_{21}. A recursive path analysis is the one where are no loops or reciprocal causes and causal flow is unidirectional [11].

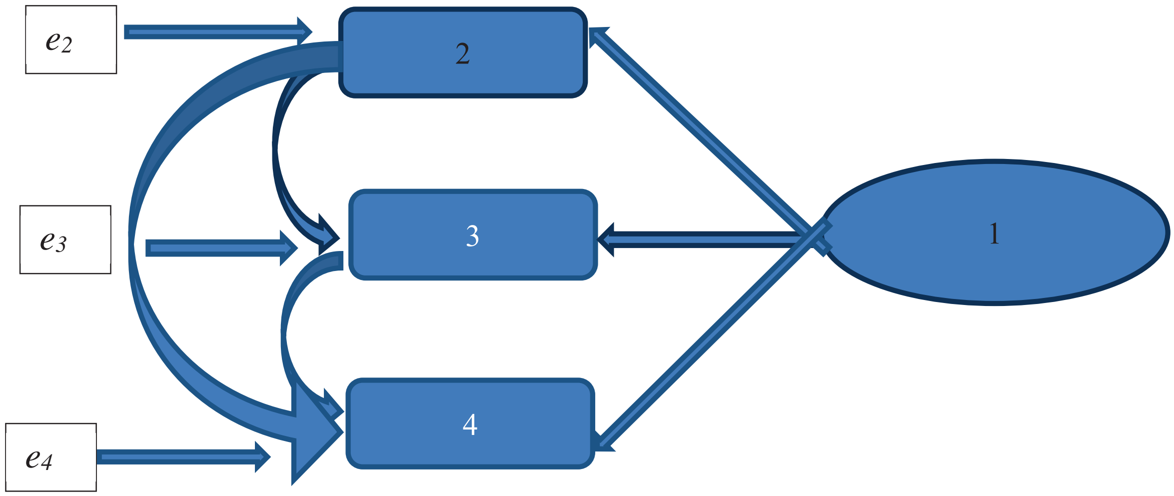

Fig. 1. An exemplar Path Model

The exogenous variable 1 indicated with no arrows is used to explain all the endogenous variables, the error term (from e_2 to e_4). More variables in the model can be explicated by using the exogenous variable one as well. There is no reverse path of causing exogenous variables to endogenous ones. This is not considered for the endogenous variables which might be a cause of any other endogenous variable. The truth of the model is considerably uncertain. Less restrictive sets of assumptions can be coped using superior models.

Calculating Path Coefficients

The variables used are in standard score form (z scores) because of the use of correlations. The variables are:

$$
\begin{aligned}
z_1 &= e_1 \\
z_2 &= p_{21}z_1 + e_2 \\
z_3 &= p_{31}z_1 + p_{32}z_2 + e_3 \\
z_4 &= p_{41}z_1 + p_{42}z_2 + p_{43}z_3 + e_4
\end{aligned}
\tag{9}
$$

In the model above (9) the first variable has not been explained by any variable. The stray causes, which are outside model causes are being indicated with e. The e might be mistaken with measurement error, but in this case, it cannot be a zero. The second variable (2) is a partial combination of variety of unexpected causes or of causes such as the first variable. The responsiveness and the connection between the equations and the path diagram must be taken in caution. Using determined paths can determine each z and lead straight to it. None of the z can be resolute by the indirect paths (e. g., there is no mention of p_{21} in the determination of z_3).

Observed correlations will help us estimate the path coefficients:

$$r_{12} = \frac{1}{N}\sum z_1 z_2 \tag{10}$$

This formula is being used for z scores in respect for r. If the path equation for z_2 is being substituted we obtain the following:

$$r_{12} = \frac{1}{N}\sum z_1 (p_{21}z_1 + e_2) = p_{21}\frac{\sum z_1^2}{N} + \frac{\sum z_1 e_2}{N} \tag{11}$$

The $\frac{\sum z_1^2}{N}$ is a standard form entry in the correlation matrix, which is the variance of z_1. In this case z_1 is 1. As a result from path analysis assumptions the correlation among z_1 and e_2 is $\frac{\sum z_1 e_2}{N}$. Therefore, handling with z scores, the path coefficient from 2 to 1 is:

$$r_{12} = p_{21} \tag{12}$$

The path coefficient and the correlation are equal, since there is only one independent variable coming from all the other variables. This provides the first path coefficient which is leading from 1 to 2. Two paths from variables 1 and 2 are leading us to variable 3. All the other paths can be calculated by simply using the correlation between the first three that have been just obtained. The error terms are left out of the calculations, because there are no correlations with any variables. As a summary;

$$r_{13} = p_{31} + p_{32} r_{12} \tag{13}$$
$$r_{23} = p_{31} r_{12} + p_{32} \tag{14}$$

etc.

We are going to use regression to obtain the path coefficients. By using simultaneous regression and treating variables 1, 2 and 3 as independent variables, and 4 as a dependent variable, we can obtain the beta weight and the true path coefficients.

A Conceptual Model of the Organizational Agility

We are going to look through a conceptual model constructed on the agility of a company in order to acquire a greater consideration of the SEM model. The theoretical framework is a significant part for the conceptual model and for the structure of the research. The correct definition of the subject and the hypothesis of the research is strictly based on the relationship between the factors. The variables from the theoretical concept are being explored by using an analytical model. Our conceptual model consists of five main parts shown in fig.2: agility drivers, enablers, obstacles, capabilities and features of an agile organization.

The agility drivers transform the business surroundings. In this way they lead the enterprise to a new situation in operating its business and looking for a competitive advantage. The agility enablers suggest the indispensable features of capabilities delivering the obligatory power for replying to modifications. The agility obstacles are all barriers, constraints, challenges in time and space as lack of particular information, etc. Flexibility, responsibility, speed and competency are the means used to represent the capabilities on an agile organization. A solution-based approach based on the customer requirements is a method used by agile organization in order to increase the customer satisfaction [9].

The empirical task performed in the research is what the conceptual model is based on. The conceptual model methodology purpose is to improve the determination of the agility-based requirements, the necessary capabilities that need to be achieved and to understand the basic concept of organizational agility.

Today's normal business environment is rapidly changing and is full of uncertainties which are affecting the company's activities. The organizations are being pressured by the environment's uncertainties and unpredicted changes. The so-called agility driver provides the organization a competitive advantage to go on at a stable position. They vary depending on the company field of interest to situation the company is put into and also this varies on how the drivers will affect the company [4].

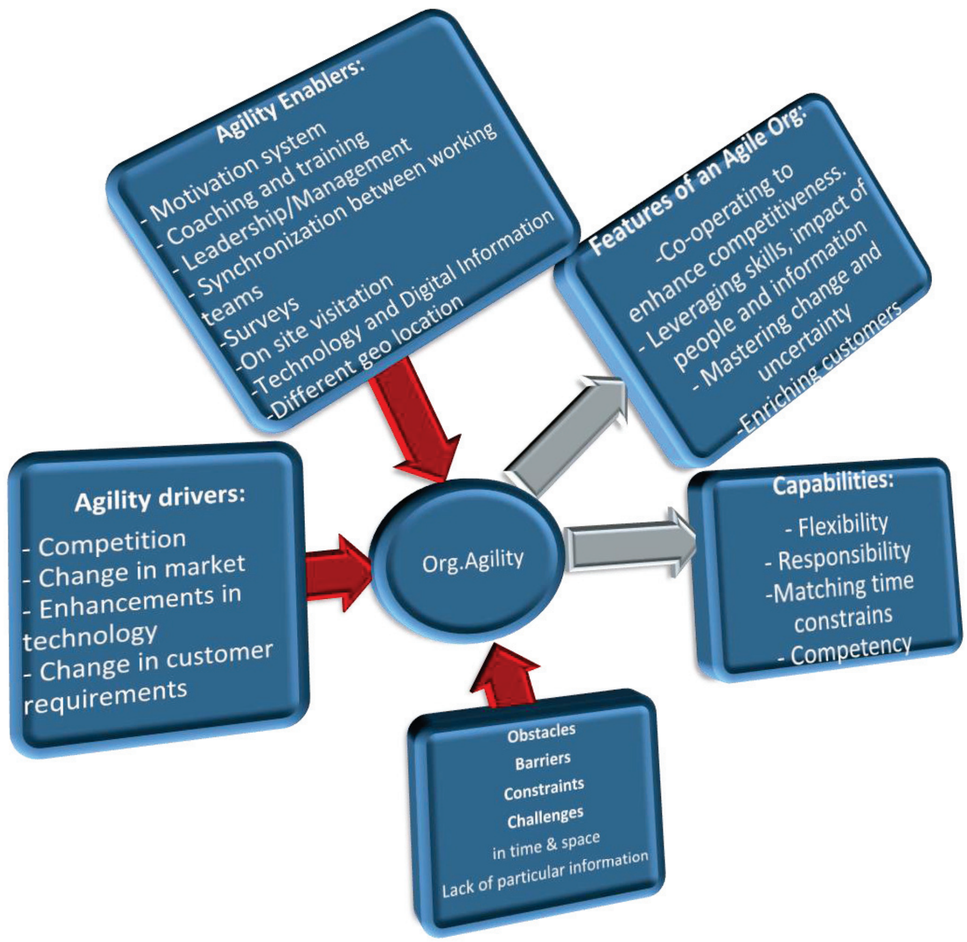

Fig. 2. A Conceptual Model of the Organizational Agility

Effects of Structural Approach for Organizational Agility Path Analysis

To define the effects that we have gained by using Path analysis in an organization that is considered agile, we need to come back to the example provided in the Path Analysis section. The effective factor can be easily determined only if the adaptable outcome could be distinct through the additional variables via path analysis, and related with other variable outcomes [12]. The influence of each variable is comprised by direct and indirect effect.

Decomposition is the degree of direct and indirect effect and the description of indirect path significance.
A variety of effects can be compared using the Standardized value in the path analysis. Standardized indirect and direct values of the effect can be compared directly. Focusing on the standardized path coefficient is sufficient to outline the significance of direct influence among two variables. The direct and indirect effect can be defined and described n path analysis when their coefficients should multiply. To compulsory express the total influence of one variable to another, the direct and indirect effect must be added together. Consequently, the rank of components could be attained through overlapping of the total effect of standardized values.

By significance organization agility factors are ranked as follows: leadership, organization commitment system, motivation through job satisfaction, improvement and empowerment, planning and evaluating performance, organizational structure flexibility, centrality, formality and complexity, team working, innovative AI technology implementation through digital transformation, virtual organization and organizational culture.

Conclusion

The striving of most modern companies to improve their organizational agility can be facilitated by using SEM methods. The gathered data can be analyzed way more precisely and to bring significantly more accurate results compared to the traditional analytical approaches. The relationship between what caused the underperformance of certain field of fields and how this is affecting the company can be presented to the managerial figures. SEM is a influential investigative tool that can help the managerial staff clear the not well performing aspects of the company and constantly increase the organizational agility.

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