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PROLOGUE TO SECOND ORDER FACTOR MODELS

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Introduction

These models could be known as the principal request models where the elements of a build (danger) were allowed to connect with the indigent variable straightforwardly. At the point when the principal request model neglects to give a satisfactory arrangement, a second-arrange model can be utilized to put a structure on the relationships between's the primary request elements (Rindskopf and Rose, 1988). The second-arrange element model suggests that there is another inactive build which administers the relationships among the principal request elements. Along these lines the main request elements are not permitted to associate, but instead their co-variety is clarified by the second request build.

However, none of the indicators were allowed to co-vary, which is the standard practice with structural equation modeling (Hatcher, 1994).

Figure 1: First order model of Project Risk

In the second order model, the five dimensions form into another latent construct, called project risk. It hypothesizes project risk as a second-order factor that explains the relationship among the five dimensions of risk. This is represented in figure 2.

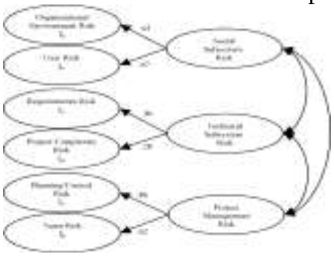

Figure 2: Second order model of Project Risk

Similarly the first order and the second order models for project risk management are shown in figure 3 and figure 4 respectively.

Plan Risk Management

Figure 3: First order model for Project Risk Management

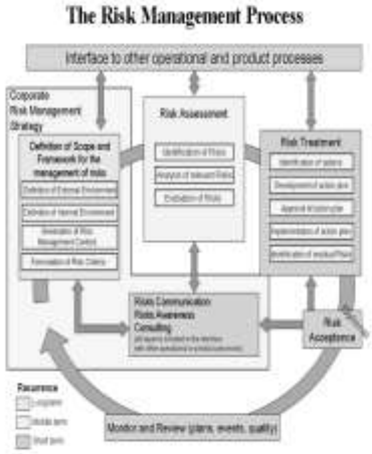

Figure 4: Second order model for Project Risk Management

Structural equation modeling is often used for testing theory associated with latent variable models because it enables the inference of complex relationships among variables which cannot be directly observed.

1.2 INTRODUCTION TO STRUCTURAL EQUATION MODELING

Auxiliary Equation Modeling (SEM) is a multivariate factual technique, which takes a corroborative way to deal with the investigation of a basic hypothesis. SEM furnishes analysts with the capacity to suit different interrelated reliance connections in a solitary model.

Advantages of SEM compared to multiple regression include more flexible assumptions (particularly allowing interpretation even in the face of multi-collinearity) the desirability of testing models overall rather than coefficients individually, the abilityto test models with multiple dependents, the ability to model mediating variables, the ability to model error terms and the ability to handle difficult data (time series with auto correlated error, non-normal data, incomplete data).

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The chi-square fit statistic. The fit measurement gives a factual test of the invalid speculation that an anticipated model fits the watched information (Hatcher, 1994). It thinks about the connection/covariance lattice that is anticipated by a model with the qualities in the watched relationship/covariance network.

RMSR The root mean square residual (RMSR) is the square root of the mean of the squared residuals (the average of the residuals between observed and predicted input matrices) (Hair et al., 1998). A RMSR value of .05 or less is usually used as an indication of very good model fit while values upto 0.1 can be taken as an indicator of moderate fit

RMSEA The root mean square error of approximation (RMSEA) attempts tocorrect the tendency of the chi square statistic to reject any model with a large sample size (Hair et al., 1998). The RMSEA is computed based on sample size and the noncentrality parameter and degrees of freedom for the proposed model (Browne and Cudeck, 1993; Steiger, 1990).

Table 1: Summary of fit measures and guidelines for their acceptable values

Indicators of fit	**Target Values**	**Target Values for**
Normed Chi-square (χ2	<4	< 5
GFI	>0.90	>0.80
AGFI	>0.80	>0.70
RMSR	<0.08	<0.10
RMSEA	<0.05	<0.08
CFI	>0.91	>0.80

1.3 EVALUATING RISK AS A SECON-DORDER CONSTRUCT

The first order and second order models of risk were shown in figure 1 and 2 respectively. Both these models were evaluated with SEM using AMOS 4.0. Table 8.1 shows the fit measures for both the models.

Table 2: Fit measures for the risk models.

Fit measures	Values for First order Model	Values for Second order model
Chi square	4389	4455
Normed chi square	3.337	3.375
GFI	0.909	0.908
AGFI	0.848	0.846
CFI	0.895	0.893
RMSR	0.084	0.084
RMSEA	0.051	0.054
Parsimony Ratio	0.952	0.958

The primary request model (estimation) of danger had numerous a larger numbers of parameters to be evaluated than the second request (hypothetical) model appeared. The principal request element model had ten connections, where the second request component model had just five waysThe ampleness of the second request model can be dictated by looking at the Target (T) coefficient (Marsh and Hocevar, 1985) where *T =chi square* (*first order* mod*el*) ÷ *chi square* (sec*ond order* mod*el*). The T coefficient has an upper bound of 1, with higher values (>0.7) implying that the relationship among the first order factors is sufficiently captured by the second order factor (Marsh and Hocevar, 1985). In that case, it can be concluded that the second-order factor model fits no worse and is preferred on the basis of parsimony (Rindskopf and Rose, 1988). Therefore, since the second-order factor model represented a more parsimonious representation of the model, it should be accepted over the first order model as a better representation of model structure.

Figure 5 shows the loadings of each of the first order factors onto the second order factor of risk. The t-values of all the loadings were significant at 1% level. These loadings, or parameter estimates, are similar to the reliability measures between a set of indicators and the construct that they measure.

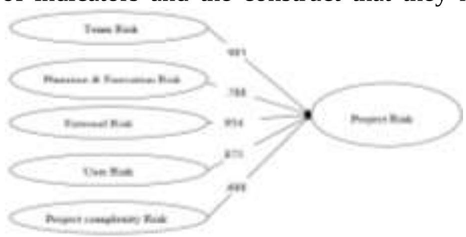

Figure 5 Parameter estimates between First and Second order factors of risk

References

1. Sammer(1998). An Organization level investigation of deliberate and automatic turn over. Foundation of Management Review 22(1), 226 – 56.
2. Queen"(2001). Measuring Software Failure Risk: Methodology and an Example. Diary of Systems Software 25(3), 257-269.
3. Saara (1986). The vital results of human asset administration. Human Resource Management 25(1), 149-167.
4. Wilson (1996). Information Privacy: Measuring Individuals' Concerns about Organizational Practices. MIS Quarterly 20(2), 167 – 196.