F Methodological Conception of the Analysis

This section is about the methodological aspects of this work. The first part describes which data is collected and how it can be characterized. After this, the basis of the quantitative analysis is shown. It comprises amongst others an introduction to modeling structural equations and the fit criteria for constructs. The following part deals with the concrete measurements of constructs and the application of the fit criteria to the measurements presented before. Finally, the cluster analysis is presented.

1 Data Collection and Data Basis

1.1 Data Collection

According to the research questions the influence of the individual's personality on his scanning and interpretation behavior has to be analyzed. Therefore, a context has to be considered in which the personality of the individual influences the organization and the early warning process to an extremely high degree. This is the case in small and medium-sized companies.[638] In these companies the CEO is responsible for early warning and corporate culture does not influence this process to a high degree.[639] However, small companies do not have significant freedom for strategic maneuver, so that strategic issues and early warning are not considered to be very important by their CEOs.[640] Therefore, medium-sized companies are analyzed, following the European Union's definition of medium-sized companies as companies with 1) a number of employees over 50 and below 250 and 2) with maximum annual sales of 50 million Euros or with a maximum balance sheet total of 43 million Euros.[641]

The second criterion for the selected organizations to be analyzed is industry. The German manufacturing industry was chosen because it is the most important industry of the German economy and, at the time of the data collection, most of the employees

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[638] See Miller and Toulouse (1986), p. 1402.
[639] See Ritvo, Salipante and Notz (1979), p. 229f.
[640] This is for example reflected by the focus of strategic management research on large businesses. See Chaganti (1987), p. 61.
[641] See Gemeinschaft (2003), p. 39.

in Germany were employed within this industry.[642] For the analysis the five most important sectors were selected:[643]

- Manufacture of transport equipment (annual sales 2004: 290 billion Euro),[644]
- Manufacture of electrical equipment (annual sales 2004: 174 billion Euro),[645]
- Manufacture of machinery (annual sales 2004: 157 billion Euro),[646]
- Food products, beverages and tobacco (annual sales 2004: 145 billion Euro),[647]
- Manufacture of chemicals, chemical products and man-made fibers (annual sales 2004: 130 billion Euro).[648]

These five sectors represent 66.6% of sales and 66.5% of employees of the manufacturing industry in Germany.[649]

A third criterion is independency from other companies such as a parent company. This criterion grants freedom in determining early warning behavior.

Table 27 provides an overview of the German organizations which fulfill all three selection criteria.[650] They are the basic population of this study.

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642 See Bundesamt' (2005), p. 101.

643 For a similar proceeding see Aust (1999), Karlshaus (2000), Dehler (2001), Frank and Reitmeyer (2003) and Steiners (2005).

644 See Bundesamt' (2005), p. 391. This sector comprises the classification numbers 34 (manufacture of motor vehicles, trailers and semi-trailers) and 35 (manufacture of other transport equipment). See Bundesamt (2003), p. 15.

645 See Bundesamt' (2005), p. 391. This sector is also called manufacture of electrical and optical equipment and comprises the classification numbers 30 (manufacture of office machinery and computers), 31 (manufacture of electrical machinery and apparatus not elsewhere classified), 32 (manufacture of radio, television and communication equipment and apparatus) and 33 (manufacture of medical, precision and optical instruments, watches and clocks). See Bundesamt (2003), p. 14f.

646 See Bundesamt' (2005), p. 391. This sector is also called manufacture of machinery and equipment not elsewhere classified. See Bundesamt (2003), p. 13.

647 See Bundesamt' (2005), p. 391. This sector comprises the classification numbers 15 (manufacture of food products and beverages) and 16 (manufacture of tobacco products). See Bundesamt (2003), p. 15f.

648 See Bundesamt' (2005), p. 391. For the classification see Bundesamt (2003), p. 8f.

649 See Bundesamt' (2005), p. 391.

650 The German Bureau of Statistics does not have a detailed report about the number of organizations per branch and size. This overview was provided by the German Federal Employment Office which examines the situation and development of employment in Germany according to professions, branches and regions. See §§ 280 and 281 SGB(III) (2005). German employers inform the German Federal Employment Office about every employee who is subject

	Size of the Organization (Employees)				Sum	Percentage
	50-100	101-149	150-199	200-249		
Transport Equipment	285	122	81	62	550	6.4%
Electrical Equipment	1,257	525	300	201	2,283	26.4%
Machinery	1,589	624	374	231	2,818	33.6%
Food Products	1,166	495	274	149	2,084	24.1%
Chemicals	467	226	132	83	908	11.5%
Sum	4,764	1,992	1,161	726	8,643	
Percentage	55.1%	23.1%	13.4%	8.4%		

Table 27: Description of the Basic Population

A large sample size is necessary to test the deduced hypotheses by analyzing the relationships between latent construct by means of factor analysis.[651] Therefore, written data collection with a standardized questionnaire is chosen as examination method because it is the most efficient way to get data from a large number of participants.[652]

In a first pretest the eight personal attitudes proposed by LEWIN and STEPHENS[653] were tested. 140 alumni of the WHU Koblenz (‘Wissenschaftliche Hochschule für Unternehmensführung’) received a survey accompanied by a personalized email. Alumni of this business school were chosen because personal attitudes of managers in general were the subject of this survey and the selected alumni were working in managerial or similar positions. The advantage of choosing alumni of this business school instead of choosing 140 CEOs of the basic population was their willingness to respond. These 140 persons were divided into two groups. One group could answer using a six-point-Likert scale, the other using a seven-point-Likert scale. A total of 54 persons participated (38.6%). 27 of the group with the six-point-Likert scale, 28 of the

to social insurance contribution. See § 28a SGB(IV) (2005). The statistics of the German Federal Employment Office comprises operating sites. An operating site (in German ‘Betriebsstätte’) is an economically and regionally defined entity. See § 9.1 SGB(IV) (2005). Following this definition, one German company may have various operating sites within Germany. Consequently, this leads to a disparity between the reported number of the German Federal Employment Office and the actual number of companies. For the empirical study it was concluded that this disparity is not very important because companies with 50 to 249 employees generally have only one operating site. Despite this disparity the statistics of the German Federal Employment Office shows the structure of German industry by indicating the number of operating sites per industry sector and size.

651 See F 2 and Homburg and Baumgartner (1995), p. 1093 and Homburg (1998), p. 78.

652 See Bortz and Döring (2003), p. 253 and 53ff. For a detailed discussion of advantages and disadvantages of this method of examination see Berekhoven, Eckert and Ellenrieder (1996), p. 112ff. and Herrmann and Homburg (1999), p. 27f.

653 See Lewin and Stephens (1994) and C 2.

group with the seven-point-Likert scale responded. For both groups the values of the fit criteria were satisfactory.[654] By means of a z-transformation the two groups were combined and, due to the improved data bases, the fit criteria were even fulfilled better. The answers included comments about unclear formulation. These were changed afterwards and MODICK's original construct, need for achievement,[655] which contains 21 items, was shortened to eight items considering aspect of formality and content. Also, the construct degree of moral reasoning was shortened.[656] In summary, the seven-point-Likert scale came up with better values for fit criteria. Additionally, the participants appreciated the possibility of neutral answers which is only possible in the case of the seven-point-Likert scale. Therefore, the seven-point-Likert scale for the final version of the questionnaire was selected.

In a second pretest five CEOs of medium-sized companies were interviewed. During these pilot interviews the expert described early warning within his organization and the industry of his organization. For each sector one CEO was selected and all classes of company sizes of the basic population were represented.

On the basis of a literature review and these pretests the questionnaire was conceptualized and then evaluated by numerous academics in the area of business administration and by other researchers in this field. The five CEOs with whom the interviews were conducted also received the questionnaire and gave feedback. The criteria to evaluate the measures were comprehensibility, completeness and neutrality of the formulation. After this, seven items had to be reformulated due to difficulties of understanding. Also structure and length of the questionnaire were evaluated.[657] It was perceived to be relatively long but appropriate to the examined subject. Additionally, the participants evaluated the structure of the questionnaire as adequate.

The addresses were provided by HOPPENSTEDT which is a company specialized in the sale of addresses of German companies to be used for direct marketing. Their database is updated daily and contains all German organizations with a minimum of sales of 20 million Euros per annum and/or a minimum of 20 employees.[658] It contains

654 See F 2.6.
655 See Modick (1977).
656 See E 3.2.6.
657 See Hunt, Sparkman and Wilcox (1982), p. 265ff. and Kinnear and Taylor (1991), p. 352ff.
658 Hoppenstedt reported 7,555 organizations for the basic population. The reported number of the German Federal Employment Office for the basic population was 8,643. This can partially be explained by the fact that a large company might have various operating sites within Germany.

the names of the CEOs, so that the questionnaire could be sent to them directly. A careful examination was necessary, however, because larger companies were listed with various sub-companies. A second selection criterion was the independence of the organizations. Only companies that were independent from a mother company were selected for the basic population.

After this re-assessment of the data, random sampling was applied according to the criteria branch and size in order to get to the organizations in the sample.

The final version of the questionnaire was sent out in May 2005 to a total of 4,500 organizations. The cover letter was personally signed by the head of the chair of management accounting and control at the EUROPEAN BUSINESS SCHOOL in Oestrich-Winkel. In order to increase the participation rate the CEOs were offered the following incentives: 1) an individual benchmarking report in which the specific early warning behavior was compared with the average of the industry, 2) the participation at a workshop with the theme ‘success factors of early warning’ and 3) the participation in a lottery to win bottles of regional wine. The quality of the database was very good as only six questionnaires came back due to wrong addresses.

1.2 Data Basis

The organizations which received the questionnaire were given three weeks to answer. Within this deadline 287 organizations responded (6.4%). After this, the CEOs who did not return the questionnaire were reminded by telephone to complete it, which took over five weeks. But this personal contact led to the participation of over 300 additional CEOs. These CEOs could also fill in the questionnaire via the internet, if requested. A total of 149 CEO filled it electronically. The attitudes of the CEOs who answered in writing and those who answered electronically did not differ significantly. The same was true for their answering behavior. Both was analyzed by means of a t-test. The completeness of all paper questionnaires was thoroughly examined. In various cases the CEOs were asked to add answers to omitted questions. The electronic version was programmed in such a manner that the participant had to answer every question. Until end of July 2005 a total of 621 respondents participated in the study. A total of 24 questionnaires had to be removed from the sample due to a misfit in the classification or the incompleteness of the questionnaire. So this study reached a sample size of 597, which corresponds to a rate of return of 13.3 %. This response rate is satisfactory, as the response rate for mailed surveys to CEOs normally ranges between 10 and 12 percent.[659]

Figure 16 and 17 show the distribution of the respondents' organizations per sector and per size.

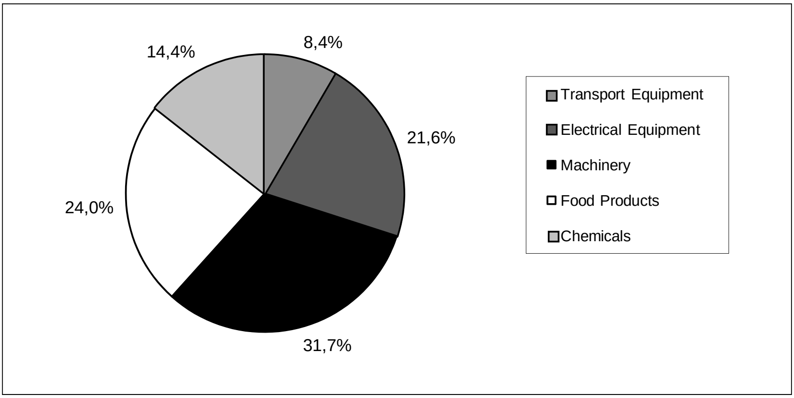

Figure 16: Characterization of Sample According to Sectors

659 See Hambrick, Geletkanycz et al. (1993), p. 407.

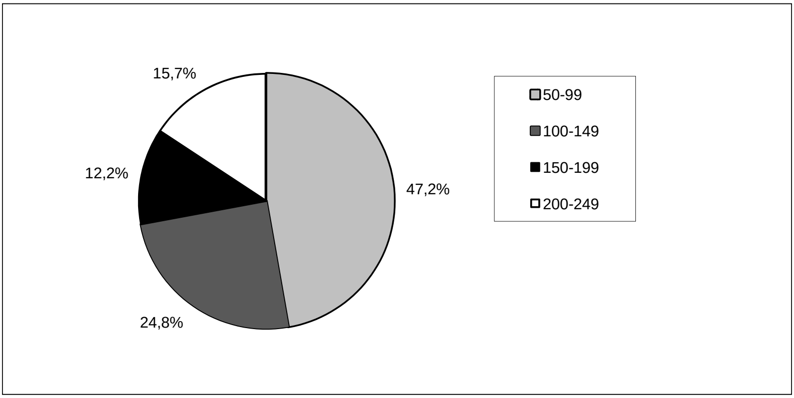

Figure 17: Characterization of Sample According to Organizational Size

The quality of the data received by the empirical investigation strongly depends on the representativeness of the sample. First, the representativeness of the sample regarding size and sectors is analyzed. Table 28 compares the respondents of the sample with the basic population according to these criteria.

	Size of the Organization (Employees)				Sum	Rate of Return	% Population
	50-100	101-149	150-199	200-249			
Transport Equipment	17	9	11	13	50	8.4%	6.4%
Electrical Equipment	48	40	23	18	129	22.6%	26.4%
Machinery	109	34	14	32	189	32.7%	33.6%
Food Products	62	40	16	25	143	24.0%	24.1%
Chemicals	46	25	9	6	86	14.4%	11.5%
Sum	282	148	73	94	597		
Rate of Return	47.2%	25.2%	12.3%	16.7%			
Percentage Population	55.1%	23.1%	13.4%	8.4%			

Table 28: Comparison of the Sample of the Study with the Basic Population

A χ^2-test can prove that the sample is representative for the basic population.[660] The result of this test was that there are no significant differences regarding size and sectors. A χ^2 value of 11.55 with 12 degrees of freedom is calculated which is far below the critical value of 21.03 for a significance level of 5%. The sample is therefore representative for the basic population.

660 See Bagozzi and Phillips (1982), p. 465 and Homburg and Giering (1996), p. 6.

The sector distribution of the sample almost coincides with the sector distribution of the population. As to size, there is apparently one important difference. Only 47% of the respondents belong to organizations with a number of employees between 49 and 100, whereas its percentage in the basic population is 55%. Within the basic population the category of organizations with a number of employees between 200 and 249 comprises 8%. But 16% CEOs managing organizations of this size answered. This mismatch can be explained by the fact that smaller organizations find the subject of early warning less important. Therefore, a lot of CEOs of smaller organizations refused to answer the questionnaire even when asked by phone.

In this context of representativeness it was also analyzed whether there is a nonresponse bias, i.e. a systematic difference between CEOs of organizations which participated in the investigation and CEOs who did not answer the questionnaire.[661] To answer the discussed question, ARMSTRONG and OVERTON assume that participants, who answer relatively late, are more similar to those who do not answer at all than to persons who answer at a very early stage. This work follows their assumption and divides the sample size into three parts depending on time of answer. Then, all the answers of the first third (organizations that answered very early) are compared with the answers of the last third (organizations that answered very late). The applied t-test allows to find medium differences of the answers. Only in two cases there was a medium difference between these groups at a significance level of 1%. Therefore, it can be concluded that no important nonresponse bias exists.

2 Basis of the Quantitative Analysis

2.1 Introduction to Modeling Structural Equations

The relationships between variables which cannot be observed directly have to be analyzed within the context of this study. The appropriate methodological means for this purpose is structural equation modeling.[662] This method is characterized by a differentiation of the variables between independent (exogenous) and dependent

[661] See Armstrong and Overton (1977).
[662] See Bliemel, Eggert, Fassott and Henseler (2005), p. 10.

(endogenous) ones in order to examine the influence of the independent on the dependent variables.[663] Modeling structural equations allows the following:[664]

1) Modeling relationships between multiple exogenous and endogenous variables[665]

2) Modeling latent variables

3) Modeling errors of measurements for observed variables[666]

4) Testing theoretically deduced hypotheses with empirical data (i.e. confirmatory analysis)[667]

There are two approaches to model structural equations: the covariance based approach and the nonlinear iterative partial least square method.[668] The covariance based approach uses the maximum likelihood function to minimize the difference between the covariance matrix of the sample[669] and the covariance matrix estimated theoretically on the basis of the structural equation.[670] Formative constructs can only be modeled by using MIMIC (multiple indicator multiple cause) or two-constructs models, which increases the number of parameters to be estimated.[671] This approach is based mainly on the theoretical works of JÖRESKOG[672] and became very popular among researchers in the field of social sciences with the software LISREL which was released in the mid-1970ies and was subsequently updated.[673] On the other hand, there is the partial least square method (PLS). Linear regressions are used to model the relationships between variables that cannot be observed directly. The values of these variables and the relationships between them are estimated by the partial least square method using an iterative way.[674] In contrast to LISREL, the partial least square method does not require a multivariate normality distribution of the parameters to be

[663] See Diamantopoulos and Siguaw (2000), p. 1.
[664] See Chin (1998), p. 297 and Fassott (2005), p. 20.
[665] See Kelloway (1998), p. 2.
[666] See Fornell (1987), p. 411.
[667] See the introduction to D.
[668] See Götz and Liehr-Gobbers (2004), p. 6f., Chin (1998), p. 295 and Fassott (2005), p. 20.
[669] See Kelloway (1998), p. 13.
[670] See Long (1983), p. 11 and Diamantopoulos and Siguaw (2000), p. 5.
[671] See Chin (1998), p. 297f., Götz and Liehr-Gobbers (2004), p. 721 and Bliemel, Eggert, Fassott and Henseler (2005), p. 10.
[672] See Jöreskog (1966), Jöreskog (1967), Jöreskog (1969) and Jöreskog (1973).
[673] See Jöreskog and Sörbom (1997).
[674] See Götz and Liehr-Gobbers (2004), p. 722.

estimated[675] and does not assume independency of observations.[676] Formative constructs can be included directly into the model. PLS was developed by WOLD,[677] JÖRESKOG's doctoral adviser.

The selection of method – LISREL or PLS – depends mainly on the nature of constructs used by the empirical investigation. Therefore, the following paragraph describes constructs in general, explains the difference between formative and reflective constructs and gives an overview about the nature of the employed constructs. Based on this knowledge, a decision about the two methods described above can be made.

2.2 Basics of Constructs

In the context of this study various aspects are examined which cannot be observed directly, for example attitudes as locus of control or need for achievement. Such complex and non-observable issues are called constructs or latent variables by literature about empirical research.[678]

The first step to measure constructs is conceptualization, e.g. the analysis and formulation of the relevant dimensions of each construct. Then, operationalization, e.g. the development of an appropriate tool of measurement, follows.[679] As latent variables cannot be directly measured, they have to be measured indirectly by means of indicators. These indicators, also called factors, are formally associated with the construct.[680] In general, single and multi-indicator constructs are distinguished. A construct with a single indicator is the easiest form of a latent variable because it is only determined by one single indicator.[681] A multi-indicator construct is represented by at least two indicators. Complex constructs should be measured by multiple indicators.[682] Multi-indicator constructs again can be differentiated in one- and multidimensional constructs. If all indicators of a construct can be assigned to one

[675] See Chin (1998), p. 297.
[676] See Fassott (2005), p. 20.
[677] See Wold (1973) and Wold (1975).
[678] See for example Bartholomew and Knott (1999), p. l.
[679] See Homburg and Giering (1996), p. 5, Churchill Jr. (1979), p. 66 and Bagozzi and Baumgartner (1994), p. 388.
[680] See Bagozzi and Phillips (1982), p. 465 and Long (1983), p. 11.
[681] See Homburg and Giering (1998), p. 115.
[682] See Churchill Jr. (1979), p. 66 and Baumgartner and Homburg (1996), p. 144.

single theoretical dimension, the construct is one-dimensional.[683] Otherwise it is multidimensional.

After the differentiation between single and multi-indicator constructs as well as between one- and multidimensional ones, the differentiation between formative and reflective constructs is presented. This classification is based on the relationship between the construct and its indicators.[684] "The direct reflective model specifies direct effects from a construct to its measures."[685] The basic nature of measuring such a reflective construct is the same for exogenous and endogenous latent variables although the models of measurement are generally specified by other variables. Therefore, the formulas for both reflective models of measurement – exogenous and endogenous latent variables – are depicted in formulas 2 and 3. Figure 18 and 19 are the corresponding graphical representations.

$$x_i = \lambda_i \cdot \xi_1 + \delta_i$$

with x_i: *Indicators of Reflective, Exogenous Variable*
ξ_1: *Reflective, Exogenous Variable*
λ_i: *Factor Loading of the Reflective, Exogenous Variable* ξ_1 *on Indicator* x_i
δ_i: *Measure Specific Random Error of Indicator* x_i

Formula 2: Measurement Model of a Reflective, Exogenous Variable

$$y_i = \lambda_i \cdot \eta_1 + \varepsilon_i$$

with y_i: *Indicator of Reflective, Endogenous Variable*
η_1: *Reflective, Endogenous Variable*
λ_i: *Factor Loading of the Reflective, Endogenous Variable* η_1 *on Indicator* y_i
ε_i: *Measure Specific Random Error of Indicator* y_i

Formula 3: Measurement Model of a Reflective, Endogenous Variable

683 See Anderson, Gerbing and Hunter (1978), p. 435 and Law and Wong (1978), p. l47.
684 See Bagozzi and Baumgartner (1994) and Bagozzi (1994).
685 Edwards and Bagozzi (2000), p. 161. See also Chin (1998), p. 305f.

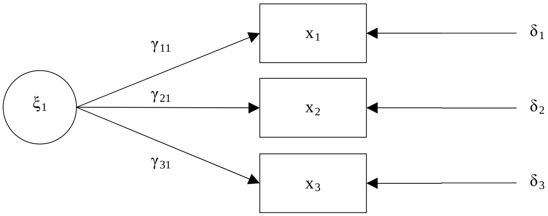

Figure 18: Measurement Model of a Reflective, Exogenous Variable

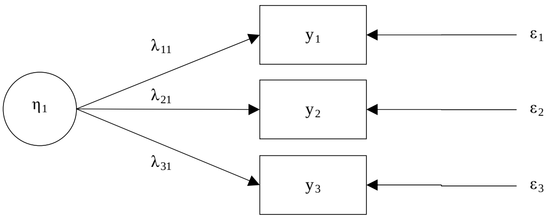

Figure 19: Measurement Model of a Reflective, Endogenous Variable

For reflective, exogenous variables all x_i measures or indicators and their variances are influenced by the construct ξ_1 and the random error δ_i. First, there is the construct common to all the measures. This is multiplied by the individual factor loading of the measure on the construct. Second, there is the random error δ_i which is specific to each x_i measure. The same is valid for reflective, endogenous variables. Only the denomination varies. The latent variable is denominated η, the measures of the indicators y_i and the random error which is specific to each y_i measure is called ε_i. The direction of causality is from the construct to the x_i (y_i) measures, and theses measures have to be correlated. This correlation is reflected by demands of internal consistency.[686] The omission of an indicator out of the measurement model does not alter the meaning of the construct.[687] To enhance this explanation an example is given and explained further.

[686] See Fornell (1982), p. 34. For reasons of clarity the correlation coefficients between the x_i (y_i) measures are not depicted in figures 18 and 19.

[687] See Jarvis, Mackenzie and Podasakoff (2003), p. 201.

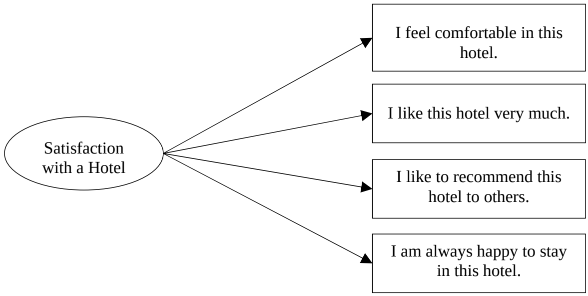

Figure 20: Example of a Reflective Construct[688]

The example shows that every single indicator of the construct 'satisfaction with a hotel' is influenced by the common construct. For this reason the presented construct is – in accordance with formulas 2 and 3 – a reflective construct.

In addition to these reflective constructs there are formative ones because "in many cases, indicators could be viewed as causing rather than being caused by the latent variable measured by the indicators."[689] The measurement of a formative construct "specifies measures as correlated causes of a construct."[690] As seen above the nature of measurement is the same for exogenous and endogenous variables. Formula 4 shows the measurement model of formative, exogenous variables, formula 5 the measurement model of formative, endogenous variables. After these formulas the measurement models of both variables are graphically presented in Figure 21 and 22.

$$\xi_1 = \pi_{\xi_1} \cdot x_i + \zeta_{\xi_1}$$

with ξ_1: *Formative, Exogenous Variable*
x_i: *Indicators of Formative, Exogenous Variable*
π_{ξ_1}: *Vector Containing Weights of Indicators* x_i
ζ_{ξ_1}: *Construct specific Random Error*

Formula 4: Measurement Model of a Formative, Exogenous Variable

[688] Adapted from Albers and Hildebrandt (2005), p. 13.
[689] MacCallum and Browne (1993), p. 533. See also Chin (1998), p. 306f.
[690] Edwards and Bagozzi (2000), p. 162.

$$\eta_1 = \pi_{\eta_1} \cdot y_i + \zeta_{\eta_1}$$

with η_1: *Formative, Endogenous Variable*
y_i: *Indicators of Formative, Endogenous Variable*
$\pi_{\eta 1}$: *Vector Containing Weights of Indicators* y_i
$\zeta_{\eta 1}$: *Construct specific Random Error*

Formula 5: Measurement Model of a Formative, Endogenous Variable

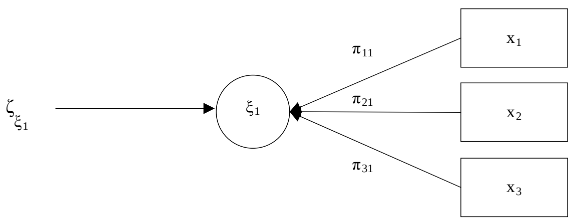

Figure 21: Measurement Model of a Formative, Exogenous Variable

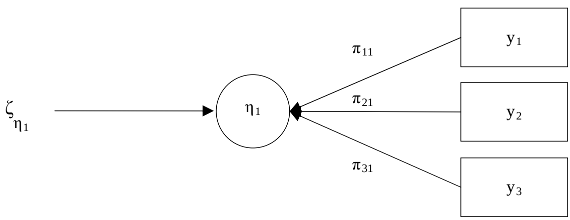

Figure 22: Measurement Model of a Formative, Endogenous Variable

Each x_i measure causes the formative, exogenous variable ξ_1 according to its weight in vector π. For formative, endogenous variables each y_i measure causes the construct η according to its weight which is part of the vector π. For both measurement models the disturbance term ζ is part of the construct. Only at construct level this measurement error is taken into account. As a consequence, the measurements of the individual indicators are assumed to be error-free. The causal relationship is opposite to the reflective model, i.e. the indicators cause the construct. So the variance of each measure is not explained by the latent variable. This causal relationship also implies that the omission of an indicator will alter the meaning of the construct. To improve the understanding of formative constructs, an example is given below in figure 23.

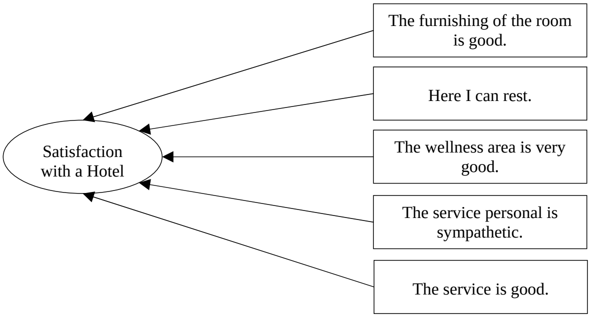

Figure 23: Example of a Formative Construct[691]

The latent variable 'satisfaction with a hotel' is determined by all of its measures. In accordance with formulas 4 and 5 it is a formative construct. Other examples of formative constructs are the construct 'social economic status', viewed as a function of background variables as income, occupational prestige and education,[692] the construct 'stress' viewed as the function of important events in life,[693] the construct 'social support' measured by various supportive incidents,[694] or the construct 'discrimination' viewed as a function of age, sex, race and disabilities.[695]

Within the context of this study the relationships between various constructs are analyzed. Reflective as well as formative constructs are used. The differentiation between formative and reflexive constructs is important in matters of fit criteria as it will be seen below. To prepare further analysis the constructs used in this work are listed below and are classified.

691 Adapted from Albers and Hildebrandt (2005), p. 13.
692 See Bollen and Lennox (1991) and Heise (1972).
693 See Cohen, Cohen, Teresi, Marchi and Velez (1990).
694 See MacCallum and Browne (1993).
695 See Bollen and Lennox (1991).

Construct	Nature	Number of Indicators	Annotation
Contingency Variables			
Perceived Strategic Uncertainty	F	21	▪ Consists of the three dimensions environmental complexity, environmental rate of change and environmental importance ▪ Each dimension is formative ▪ PSU is the product of environmental uncertainty (complexity plus rate of change) and environmental importance
Locus of Control	R	6	
Tolerance for Ambiguity	R	8	
Need for Achievement	R	8	
Risk Propensity	R	4	
Egalitarianism	R	6	
Moral Reasoning	R	7	
Machiavellianism	R	8	
Trust in People	R	5	
Design Variables			
Internal, Personal Sources	F	7	
Internal, Impersonal Sources	F	7	
External, Personal Sources	F	7	
External, Impersonal Sources	F	7	
Personal Sources	F	14	Personal sources are the sum of internal, personal and external, personal sources
Impersonal Sources	F	14	Impersonal sources are the sum of internal, impersonal and external, impersonal sources
External Sources	F	14	External sources are the sum of external, personal and external, impersonal sources
Internal Sources	F	14	Internal sources are the sum of internal, personal and internal, impersonal sources
Scanning Frequency	F	28	Sum of all four sources
Scope of Scanning	F	7	
Degree of Delegation	F	7	
Diversity of Internal Models	F	8	
Intensity of Interpretation	R	2	
Degree of Tool Support	F	1	
Fixity of Time for Interpretation	F	1	
Success Variables			
Success of Early Warning	F	7	
Economic Success	F	2	
F = Formative; R = Reflective			

Table 29: Overview of Constructs Used

2.3 Selection of Method for Structural Equation Modeling

This study has shown that two approaches for structural equation modeling exist: the covariance approach of LISREL and the partial least square method (PLS). LISREL can only include formative constructs by using MIMIC (multiple indicator multiple cause) or two-constructs models. This increases the number of parameters to be estimated.[696] As the majority of constructs, analyzed within the context of this study, is formative, PLS as the method for the analysis of the here presented empirical data was chosen. The advantage of this choice is that the two difficult assumptions of the covariance approach, i.e. multivariate distribution of the variables and independency of observations,[697] do not have to be considered.

2.4 The Structural Model as Means of Valuating Simple Causal Hypotheses

2.4.1 Overview

The basis of analyzing the relationships of latent constructs with PLS is a structural (equation) model. Such a model displays the theoretically assumed relationships between latent variables. The independent variables are called exogenous variables and influence the dependent ones, called endogenous variables. The model is recursive, i.e. no circular relationship is allowed.[698] Below an example of a structural model is provided.

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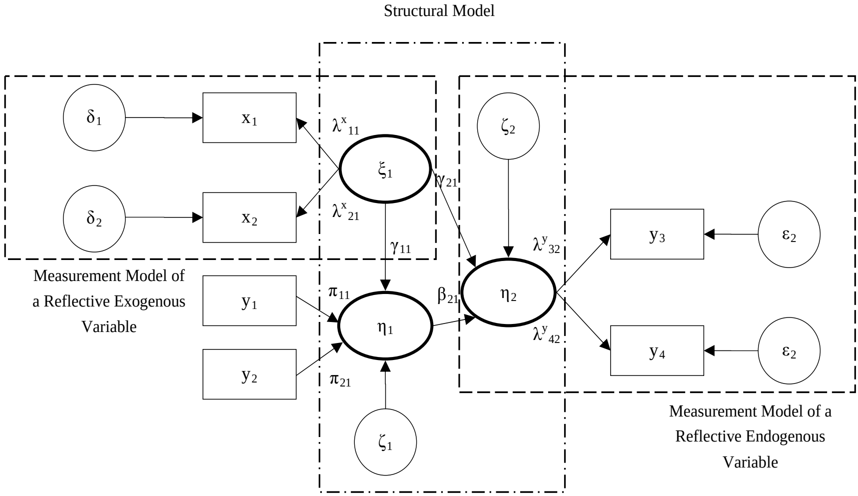
696 See Götz and Liehr-Gobbers (2004), p. 721 and Bliemel, Eggert, Fassott and Henseler (2005), p. 10. LISREL sums up the values of the single indicators, forms an average and operates with a single index variable. Consequently the influence of a single indicator cannot be analyzed. Therefore, the covariance structure analysis does not allow the figuration of formative constructs. See Fassott (2005), p. 25 and the sources mentioned there.

697 See Chin (1998), p. 297 and Fassott (2005), p. 20.

698 See Götz and Liehr-Gobbers (2004), p. 716.



with ξ_1: *Reflective, Exogenous Variable*
$x_{1,2}$: *Indicators of Reflective, Exogenous Variable*
λ^x_{i1}: *Factor Loading of Reflective, Exogenous Variable ξ_1 on Indicators $x_{1,2}$*
$\delta_{1,2}$: *Measure Specific Random Error of Indicators $x_{1,2}$*
$\eta_{1,2}$: *Endogenous Variables*
$y_{1,2}$: *Indicators of Endogenous, Formative Variable*
$\pi_{\eta 1}$: *Vector Containing Weights of Indicators $y_{1,2}$*
$\zeta_{\eta i}$: *Construct specific Random Error*
$y_{3,4}$: *Measures of the Reflective, Endogenous Variable η_2*
λ^y_{i2}: *Factor Loading of the Reflective, Exogenous Variable η_2 on Indicators $y_{3,4}$*
$\varepsilon_{1,2}$: *Measure Specific Random Error of Indicators $y_{3,4}$*
γ_{i1}.: *Causal Relationship between ξ_1 and Endogenous Variables i*
β: *Causal Relationship between Endogenous Variables*

Figure 24: Simple Structural Model

Three constructs (ξ_1, η_1, η_2) are depicted. Arrows show the relationships between them. ξ_1 as the exogenous variable is not influenced by any other latent variable and influences η_1 and η_2. Additionally, η_1 influences η_2. Each of the constructs is measured by two indicators (x_1, x_2; y_1, y_2; y_3, y_4). ξ_1 and η_2 are reflective constructs and η_1 is a formative one. This structural model also has a standardized, mathematical form:

$$\eta = B\eta + \Gamma\xi + \zeta$$

with η: *Vector Containing Values of Endogenous Variables*
B: *Matrix of the Relationship between the Endogenous Variables*
Γ: *Matrix of the Relationship between Exogenous and Endogenous Variables*
ξ: *Vector Containing Exogenous Variables*
ζ: *Vector Containing Measurement Errors of the Endogenous Variables*

Formula 6: Standardized Form of a Structural Equation

Such structural equations or models are subject to fit criteria. These criteria help to valuate these models and will be presented in the following paragraph.

2.4.2 Fit Criteria for Structural Models

In order to determine fit criteria for structural models the criteria proposed by GÖTZ and LIEHR-GOBBERS[699] will be followed. They propose three fit criteria for structural models: 1) coefficient of determination, 2) reliability of path coefficients and 3) effect size.

The coefficient of determination R^2 shows the part of variance of the latent, endogenous variable explained by the exogenous ones. It measures the quality of fit of the regression function.[700] R^2 is a standardized value between 0 and 1. The higher the part of the variance of the endogenous variable explained by the measured exogenous variables, the more the value will approach to 1. This value also depends on the numbers of exogenous variables. Therefore, a general minimum value is difficult to assert. However, a minimum value of 0.3 should be attained.[701]

The second criterion is the reliability of the path coefficients. They describe the influence of the exogenous variables on the endogenous one and can be interpreted as standardized beta-coefficients of a regression analysis. The reliability of the path coefficients is analyzed by t-statistics. PLS generates these values using resampling methods to asses the accuracy of the path coefficients. A significance of 1% corresponds to a t-value over 2.326, a significance of 5% to a t-value between 1.645 and 2.326, finally a significance of 10% to a t-value between 1.282 and 1.645. This is the case of a one-tailed test.[702] Only when path coefficients are significant, a statistically significant relationship between variables exists. On the basis of these path coefficients and of the level of significance hypotheses can be confirmed or rejected.

The last criterion, the effect size f, analyzes whether an exogenous variable has a significant influence on the endogenous one. This means that the explanatory contribution of the exogenous variable can be analyzed. COHEN developed this concept by comparing the coefficient of determination R^2 of the structural model

[699] See Ibid., p. 730f.
[700] See Craney and Surles (2002), p. 392.
[701] See Cohen, Cohen, West and Aiken (2003), p. 3.
[702] See Homburg and Baumgartner (1998), p. 360f.

inclusive the analyzed exogenous variable with the coefficient of determination R^2 of the structural model exclusive the analyzed exogenous variable.[703] The formula is given below:

$$f = \frac{R^2_{incl} - R^2_{excl}}{1 - R^2_{incl}}$$

with R_{incl}: *Coefficient of Determination R^2 of the Structural Model Inclusive the Analyzed Exogenous Variable*

R_{excl}: *Coefficient of Determination R^2 of the Structural Model Exclusive the Analyzed Exogenous Variable*

Formula 7: Effect Size

Based on CHIN et al.,[704] COHEN et al.[705] and GÖTZ and LIEHR-GOBBERS[706] three classes of influence can be differentiated. They are a) significant influence ($0.075 > f \geq 0.01$), b) highly significant influence ($0.25 > f \geq 0.075$) and c) very highly significant influence for $f \geq 0.25$.

To conclude this explanation of fit criteria calculated by PLS for structural models an overview is given:

Criteria	**Aspiration Level**
Coefficient of Determination R^2	≥ 0.3
T-Value of Path Coefficients	$1.645 > t \geq 1.282$ → Significance Level of 10 % $2.326 > t \geq 1.645$ → Significance Level of 5 % $t \geq 2.326$ → Significance Level of 1 %
Effect Size f	$0.075 > f \geq 0.001$ → Significant Influence $0.25 > f \geq 0.075$ → Highly Significant Influence $f \geq 0.25$ → Very Highly Significant Influence

Table 30: Overview of Fit Criteria for Structural Equations

2.5 Moderating Effects as Means of Valuating Alignment Hypotheses

2.5.1 Introduction to Moderating Effects

The analysis of moderating variables is to analyze the influence of an additional exogenous variable on the causal relationship between an exogenous variable and an endogenous one. “In general terms, a moderator is a qualitative (e.g. sex, race, class)

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703 See Cohen, Cohen, Teresi, Marchi and Velez (1990), p. 8ff. and p. 410ff. and Chin (1998), p. 316.
704 See Chin, Marcolin and Newsted (2003), p. 195f.
705 See Cohen, Cohen, Teresi, Marchi and Velez (1990), p. 410ff.
706 See Götz and Liehr-Gobbers (2004), p. 731.

or quantitative (e.g. level of reward) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable."[707] If a variable is a moderating variable it will change the direction or the intensity of a causal relationship within a structural model. Such an effect is also called effect of interaction. These moderators and their effects are very important because causal relationships are often influenced by additional variables.[708] Figure 25 shows that moderating variables influence the causal relationship between an exogenous and an endogenous variable.Moder

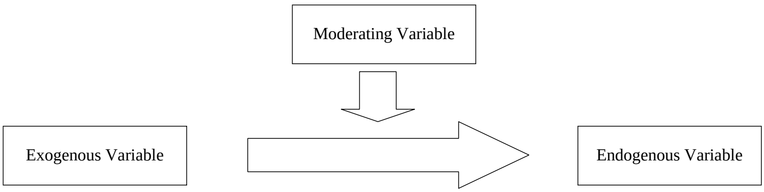


Figure 25: Moderating Effect[709]

2.5.2 Modeling Moderating Effects in the Context of the PLS Method

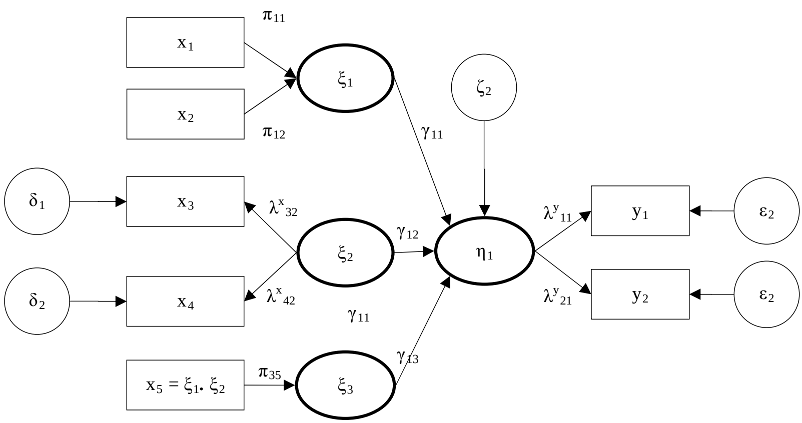
Empirical research often ignores the effect of interaction[710] or avoids it with an artificial dichotomy and uses dummy variables.[711] PLS is capable to model these effects and can consider them as part of structural models. The analysis of moderating effects is similar to that of a moderated regression.

In case of a moderating effect the structural model is expanded by an additional exogenous variable. This variable is the product of the moderating variable and the other exogenous one which interacts with the endogenous variable. This product is called interaction term. Following CHIN et al.[712] and GÖTZ and LIEHR-GOBBERS[713] one has to distinguish between the effects of interaction caused by reflective and formative constructs. In the context of this study the moderating variable in question – success of early warning – is a formative construct. Therefore, the method for analyzing formative constructs as moderating variables is presented now. First, the

707 Baron and Kenny (1986), p. 104.
708 See Chin, Marcolin and Newsted (2003), p. 193.
709 See Eggert, Fassott and Helm (2005), p. 104.
710 See Homburg and Giering (2001), p. 47.
711 See Yasai-Ardekani and Nystrom (1996), p. 195.
712 See Chin, Marcolin and Newsted (2003), p. 198f.
713 See Götz and Liehr-Gobbers (2004), p. 725.

weights of the indicators which form the formative construct that is supposed to be a moderator have to be calculated by PLS. If the exogenous variable is reflective, its factor loadings have to be considered. If it is formative, the weights of its indicators have to be regarded. Then, the structural model is expanded by the product of the interacting variables, i. e. moderating and exogenous variable. Both, the interaction term and the moderating variable, are modeled as exogenous variables influencing the endogenous one. Based on the structural model, PLS calculates the interaction effect of the moderating variable. It shows the degree of moderation and is valued by 1) the path coefficients and their level of significance and 2) its effect size. The criteria for both are the same as the fit criteria for structural models is presented in F 2.4.2.

Figure 26 shows a structural model that contains the interaction term for a formative construct and the moderating variable as additional exogenous variables.



with x_i: *Indicators of Exogenous Variables*
δ_i: *Measure Specific Random Error of Indicators* $x_{3,4}$
λ^x_{i2}: *Factor Loading of Reflective, Exogenous Variable* ξ_2 *on Indicators* $x_{3,4}$
λ^y_{i1}: *Factor Loading of Reflective, Endogenous Variable* η_1 *on Indicators* $y_{1,2}$
$\pi_{\xi i}$: *Vector Containing Weights of Indicators*
ξ_1: *Moderating Variable*
ξ_2: *Reflective, Exogenous Variable*
ξ_3: *Interaction Term*
η_1: *Reflective, Endogenous Variable*
ε_i: *Measure Specific Random Error of Indicators* $y_{1,2}$
ζ: *Construct Specific Random Error of Endogenous Variable*
$\gamma_{\eta\xi}$: *Path Coefficients of Relationship between Exogenous Variables* ξ *and Endogenous Variable* η_1

Figure 26: Structural Model Containing a Term of Interaction[714]

[714] See Ibid., p. 724.

The model presented in figure 26 can be described formally. Formula 8 explains how the endogenous variable is influenced by the exogenous one, the term of interaction and the moderating variable.

$$(\eta_1)=(\gamma_{11}\gamma_{12}\gamma_{13})\begin{pmatrix}\xi_1\\ \xi_2\\ \xi_3\end{pmatrix}+(\zeta_1)$$

with	η_1:	*Reflective, Endogenous Variable*
	$\gamma_{\eta\xi}$:	*Path Coefficients of Relationship between Exogenous Variables and Endogenous Variable*
	ξ_1:	*Moderating Variable*
	ξ_2:	*Reflective, Exogenous Variable*
	ξ_3:	*Term of Interaction*
	ζ_1:	*Construct Specific Random Error of Reflective, Exogenous Variable*

Formula 8: Causal Relationship between Exogenous Variables and an Endogenous Variable in Case of Moderating Effect

2.5.3 Valuation of Alignment Hypotheses

Alignment hypotheses in the context of the contingency theory predict in general that successful organizations adapt their organizational structure to contingency variables. In the specific context of this study alignment hypotheses suppose that successful organizations adapt their scanning and interpretation behavior to perceived strategic uncertainty more than unsuccessful organizations.[715] Therefore, it is necessary to analyze whether success of early warning intervenes as a moderating variable. For this, it needs to be judged whether success influences the causal relationship between perceived strategic uncertainty and early warning behavior.[716]

Having studied structural models in general and moderating effects within such structural models, the fit criteria for constructs applied in these models are presented.

2.6 Fit Criteria for Constructs

A high quality of measuring complex constructs is the basis of good empirical work in general[717] and the necessary condition to analyze relationships of dependency.[718]

[715] See hypotheses 2b, 3b 4b, 5b, 6b, 7b, 8b, 9b, 10b and 11b.
[716] See Yasai-Ardekani and Nystrom (1996), p. 197.
[717] See Peter (1979), p. 6, Churchill Jr. (1979), p. 64ff. and Anderson and Gerbing (1988), p. 411f.
[718] See Homburg and Pflesser (1999), p. 415f.

Therefore, fit criteria for constructs have to be considered. In the following paragraph the fit criteria for reflective constructs, then the criteria for formative ones will be presented. The criteria proposed by GÖTZ and LIEHR-GOBBERS[719] who developed criteria which are exhaustive for the analysis of fitness of reflective and formative constructs within the context of PLS are followed.

2.6.1 Fit Criteria for Reflective Constructs

In a model of reflective measurement a latent variable becomes operationalized by means of various indicators. These indicators are measured by an indicator specific error. In order to judge the quality of a reflective construct, one has to analyze the extent the indicators represent the characteristics of the construct and the extent the measurement of these indicators is influenced by errors.

To determine the extent of the criteria reliability and validity is introduced. In this context, the measurement error of every single indicator has to be divided into a systematic and a random error. The random error is explained by factors which influence the measurement non-systematically. The systematic error, in contrast, is independent of randomness and occurs identically at every repetition of the measurement.[720]

If there is no random error, the measurement is completely reliable and the measurement is formally correct.[721] Therefore, complete reliability means that a measurement is reproducible under constant conditions of measurement with a result that is free from random error.[722] The more reliable a measurement, the more the variance of the indicator can be explained by the influence of the construct.[723] The second criterion, validity, is the degree of conceptual correctness of the measurement. It is valid if it measures what it pretends to measure.[724] This signifies that a measurement is completely valid if there is neither a random nor a systematic error. As a reliable measurement only implies the absence of a systematic error and a valid measurement implies the absence of both, the random and the systematic error,

[719] See Götz and Liehr-Gobbers (2004), p. 730f.
[720] See Churchill Jr. (1987), p. 381 f.
[721] See Berekhoven, Eckert and Ellenrieder (1996), p. 87.
[722] See Peter (1979), p. 6 and Churchill Jr. (1987), p. 495.
[723] See Nieschlag, Dichtl and Hörschgen (1997), p. 722ff.
[724] See Churchill Jr. (1979), p. 65.

reliability can be regarded as a necessary but not sufficient condition for validity. For further analysis of reliability and validity the following four criteria are analyzed.[725]

Content validity describes the degree to which indicators of the measurement model belong to the construct. For this, the content of the construct has to be considered. The items should reflect all facets of the meaning of the construct.[726] As there are no intersubjective criteria for the control of content validity it is considered as a general concept which underlies the development and analysis of constructs.[727]

The variance of indicators can be explained with the underlying latent variable. **Indicator reliability** measures how important the influence of a construct is. A common fit criterion is that a minimum of 50% of the variance of the indicator has to be explained by the underlying latent variable.[728] This implies that the weights λ of the latent variable on the indicators x_i (for exogenous variables) and y_i (for endogenous variables) are greater than 0.7. If this criterion is fulfilled, the variance of the indicator determined by the construct is greater than the variance determined by the error of measurement.[729] For newly developed scales values far below 0.7 can be expected.[730] Nevertheless, also for such constructs a minimum value for indicator reliability of 0.4 has to be trespassed.[731] Otherwise the indicator has to be eliminated. Indicators with indicator reliability between 0.4 and 0.7 do not have to be eliminated if the value of the internal consistency is above 0.7.[732]

Whereas indicator reliability measures the reliability of the measurement on the indicator level, construct reliability measures the quality of the model on the construct level.[733] Construct reliability is high if the relationship between the indicators is high. It is measured by the value of **internal consistency**.[734] FORNELL and LARCKER's definition is shown below:

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725 See Götz and Liehr-Gobbers (2004), p. 727f.
726 See Bohrnstedt (1970), p. 92.
727 See Schnell, Hill and Esser (1993), p. 163.
728 See Homburg and Giering (1996), p. 12.
729 See Götz and Liehr-Gobbers (2004), p. 727 and Carmines and Zeller (1979), p. 27.
730 See Hulland (1999), p. 198.
731 See Götz and Liehr-Gobbers (2004), p. 727 and Homburg and Baumgartner (1995), p. 170.
732 See Hulland (1999), p. 198.
733 Therefore, this value has more impact than reliability criteria at the level of the indicators. See Bagozzi and Baumgartner (1994), p. 402 and Chau (1999), p. 218f.
734 See Götz and Liehr-Gobbers (2004), p. 727. It is a measure similar to Cronbach's alpha. The internal consistency was chosen for its two advantages. In contrast to Cronbach's alpha, internal consistency considers the factor loadings of the indicators. In contrast, these loadings are all

$$\text{Internal Consistency} = \frac{\left(\sum_i \lambda_{ij}\right)^2}{\left(\sum_i \lambda_{ij}\right)^2 + \sum_i \operatorname{var}\left(\varepsilon_{ij}\right)}$$

with j: *Continuous Index for the Reflective Measurement Model*
i: *Continuous Index for the Indicators of the Reflective Measurement Model*
λ_{ij}: *Weight of the Latent Variables j on its Indicators i*
ε_i: *Measure Specific Random Error of Indicator i*

Formula 9: Internal Consistency[735]

The value of internal consistency can vary between 0 and 1. BAGOZZI and YI consider a minimum level of 0.6 as acceptable.[736] This study follows GÖTZ and LIEHR-GOBBERS who demand a minimum value of 0.7.[737] If the value of internal consistency is below the required minimum, indicators with low correlation to other indicators have to be eliminated.[738] This can be done by looking at the item-to-total correlation of the indicators. The single item-to-total correlation is defined as the correlation of an indicator (= item) with the sum of all indicators (= total). In contrast, the corrected item-to-total correlation is the correlation of an indicator with the sum of the remaining indicators after the considered indicator has been removed.[739] In the context of this work the more sophisticated corrected item-to-total correlation is employed and the attribute corrected is omitted.[740] In general, item-to-total correlations should be as high as possible. The item-to-total correlation is used as the criterion to select the indicator which has the lowest relationship with the construct. This indicator then is eliminated in order to increase internal consistency.[741] The procedure of elimination has to be repeated if the value of internal consistency is still below the minimum value.

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equally valued by the calculation of Cronbach's alpha. Additionally, the value of Cronbach's alpha correlates with the number of indicators which is not the case for internal consistency. See Götz and Liehr-Gobbers (2004), p. 734.

735 See Fornell and Larcker (1981), p. 45.

736 See Bagozzi and Yi (1988), p. 82.

737 See Götz and Liehr-Gobbers (2004), p. 727. They base their minimum level on Nunnally (1978), p. 245.

738 See Götz and Liehr-Gobbers (2004), p. 728.

739 See Norušis (1993), p. 146.

740 See Churchill Jr. (1979), p. 68f.

741 See Ibid., p. 68.

The final step of this fit analysis is the examination of **discriminance validity**. Within the measurement models various latent constructs are measured. The dissimilarity of theses measurements then is analyzed by means of the discriminance validity. The variance of the latent variable with its indicators has to be higher than the variance with any other latent variable.[742] First, the variance between the latent variable and its indicators – the average explained variance – has to be taken into account. Formula 10 shows its calculation.

$$AEV = \frac{\sum \lambda_i^2}{\sum_i \lambda_i^2 + \sum_i \operatorname{var}(\varepsilon_i)}$$

with *AEV:* *Average Explained Variance*
λ_i: *Weight of a Latent Variable j on its Indicator i*
ε_i: *Measure Specific Random Error of Indicator i*

Formula 10: Average Explained Variance

The measurements of the latent variables differ, e.g. the problem of multidiscriminancy does not exist, if the average explained variance is higher than the squared correlation between the latent variable and any other latent variable used in the investigation.[743]

Table 31 summarizes the fit criteria for reflective latent variables.

Criteria	**Aspiration Level**
Indicator Reliability	≥ 0.7 (when the construct is newly developed or internal consistency ≥ 0.7, the minimum value is 0.4)
Internal Consistency	≥ 0.7
Item-to-Total Correlation	If internal consistency < 0.7, elimination of indicator with lowest item-to-total correlation
Average Explained Variance	Must be higher than the squared correlation between the latent variable and any other latent variable

Table 31: Overview of Fit Criteria for Reflective Constructs

742 See Hulland (1999), p. 199.
743 See ibid., p. 199.

2.6.2 Fit Criteria for Formative Constructs

The criteria presented above can only be applied to reflective constructs.[744] Formative constructs have to be tested in a different way. Of the criteria described above only indicator reliability is applicable to formative constructs. Due to the fact that every indicator defines the formative latent construct and that therefore, a correlation between the indicators can be positive, negative or non-existent, content validity,[745] construct validity[746] and discriminance validity[747] cannot be applied to formative constructs. Two other tests have to be conducted.

In the context of **indicator reliability** the weights of the indicators, which are allocated to them by PLS have to be compared. This analysis helps to understand which indicators are most relevant to define the latent construct.[748] As stated above, the indicators of a formative latent construct may have positive, negative or no correlation with other indicators. Therefore, their weights on the latent variable cannot be considered as factor loadings. The values of the weights are relatively small in comparison with values of factor loadings. This is for the PLS technique that allocates the values to the indicators in order to maximize the explained variance of the latent variable. In consequence, small weights cannot be interpreted as evidence for a weak measurement model.[749] Moreover, no indicator can be eliminated due to a small weight because each single indicator defines the latent variable.[750]

Although high correlations between the indicators of a formative construct need not to be considered, **multicollinearity** can be a problem.[751] It is undesirable and arises if one indicator is a linear function of another indicator.[752] GÖTZ and LIEHR-GOBBERS

744 See Bollen (1989), Kim and Mueller (1971), Nunnally (1978), Harman (1976) and Long (1983).
745 See Götz and Liehr-Gobbers (2004) and the sources cited there: Bollen and Lennox (1991), Cohen, Cohen, Teresi, Marchi and Velez (1990) and Chin and Gopal (1995).
746 See Götz and Liehr-Gobbers (2004), p. 729 and Hulland (1999), p. 201, Krafft (1999), p. 124f. and Rossiter (2002), p. 307f.
747 See Götz and Liehr-Gobbers (2004), p. 730 and Fornell and Larcker (1981), p. 46.
748 See Sambamurthy and Chin (1994), p. 231f.
749 See Götz and Liehr-Gobbers (2004), p. 729 and Chin (1998), p. 307.
750 See Götz and Liehr-Gobbers (2004), p. 729, Bollen and Lennox (1991), p. 308 and Jarvis, Mackenzie and Podasakoff (2003), p. 202.
751 See Grewal, Cote and Baumgartner (2004).
752 See Cohen, Cohen, West and Aiken (2003), p. 6 and Backhaus, Erichson, Plinke and Weiber (2005), p. 88ff.

propose the variance inflation factor to determine multicollinearity.[753] It is defined as:[754]

$$VIF_i = \frac{1}{1 - R_i^2}$$

with *VIF:* *Variance Inflation Factor*
i: *Indicator of the Construct*
R^2_i: *Multiple Coefficient of Determination of Indicator i on all other Indicators*

Formula 11: Variance Inflation Factor

Values over 10 signal multicollinearity.[755] Table 32 summarizes the fit criteria for formative constructs:

Criteria	**Aspiration Level**
Indicator Reliability	Analysis of the weights of the indicators
Multicollinearity	VIF $\geq$ 10

Table 32: Overview of Fit Criteria for Formative Constructs

3 Construct Measuring

In the following analysis the fit criteria presented above are applied to the constructs used in this study.

3.1 Early Warning Behavior

3.1.1 Scanning

3.1.1.1 Scanning Frequency and Sources

Scanning frequency comprises four possible sources of scanning. These four constructs are presented below. The composite constructs internal sources (internal, personal plus internal, impersonal sources), external sources (external, personal plus external, impersonal sources), personal sources (internal, personal plus external, personal sources), impersonal sources (internal, impersonal plus external, impersonal sources) and frequency (all four sources), however, are listed in the appendix.

753 See Götz and Liehr-Gobbers (2004), p. 729. For alternative measures see Willan and Watts (1978).
754 See Craney and Surles (2002), p. 392 and Ukourmunne, Gulliford and Chinn (2002), p. 479.
755 See Götz and Liehr-Gobbers (2004), p. 729 and Craney and Surles (2002), p. 392f.

Internal, Personal Sources

Information about the Indicators of the Construct 'Internal, Personal Sources'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.41	0.61
Technologien	0.41	0.61
Wettbewerber	0.46	0.75
Rohstoffe/Zulieferer	0.48	0.75
Politisch/rechtlicher Bereich	0.41	0.61
Wirtschaftliche Rahmenbedingungen	0.46	0.75
Soziokultureller Bereich	0.48	0.75
VIF: Variance Inflation Factor		

Table 33: Information about the Construct 'Internal, Personal Sources'

All sectors determine the construct internal, personal sources in the same way. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

Internal, Impersonal Sources

Information about the Indicators of the Construct 'Internal, Impersonal Sources'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.49	1.46
Technologien	0.30	1.59
Wettbewerber	0.19	1.55
Rohstoffe/Zulieferer	0.53	1.43
Politisch/rechtlicher Bereich	0.17	2.81
Wirtschaftliche Rahmenbedingungen	0.27	2.61
Soziokultureller Bereich	0.20	1.85
VIF: Variance Inflation Factor		

Table 34: Information about the Construct 'Internal, Impersonal sources'

The construct internal, impersonal sources is mainly determined by data about suppliers as well as clients. Data about competitors, the political/legal and the socio-cultural sector do not determine the construct to an important degree. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

External, Personal Sources

Information about the Indicators of the Construct 'External, Personal Sources'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.71	1.87
Technologien	0.39	1.96
Wettbewerber	0.71	1.87
Rohstoffe/Zulieferer	0.69	1.65
Politisch/rechtlicher Bereich	0.59	2.18
Wirtschaftliche Rahmenbedingungen	0.20	2.19
Soziokultureller Bereich	0.38	1.75
VIF: Variance Inflation Factor		

Table 35: Information about the Construct 'External, Personal Sources'

The construct external, personal sources is mainly determined by data about customers, competitors, suppliers and political/legal conditions. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

External, Impersonal Sources

Information about the Indicators of the Construct 'External, Impersonal Sources'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.63	1.46
Technologien	0.41	1.55
Wettbewerber	0.64	1.41
Rohstoffe/Zulieferer	0.33	1.48
Politisch/rechtlicher Bereich	0.55	3.19
Wirtschaftliche Rahmenbedingungen	0.59	3.06
Soziokultureller Bereich	0.33	2.00
VIF: Variance Inflation Factor		

Table 36: Information about the Construct 'External, Impersonal Sources'

This construct is mainly determined by data about clients and competitors. External, impersonal sources also provide data about the political/legal and the economic sectors of the general environment. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

3.1.1.2 Scope of Scanning

Scope of Scanning

Information about the Indicators of the Construct 'Scope of Scanning'		
Description of Indicators	*Weight*	*VIF*
Informationen über das Verhalten potenzieller Kunden	0.41	1.40
Informationen über allgemeine technologische Entwicklungen, die Ihr Unternehmen nicht direkt betreffen	0.29	1.28
Informationen über potenzielle Wettbewerber	0.45	1.62
Informationen über potenzielle Zulieferer	0.38	1.32
Informationen über allgemeine politische und gesetzgeberische Entwicklungen, die Ihr Unternehmen nicht direkt betreffen	0.33	1.96
Informationen über allgemeine wirtschaftliche Entwicklungen, die Ihr Unternehmen nicht direkt betreffen	0.04	2.12
Informationen über allgemeine soziokulturelle Entwicklungen, die Ihr Unternehmen nicht direkt betreffen	0.28	1.81
VIF: Variance Inflation Factor		

Table 37: Information about the Construct 'Scope of Scanning'

The construct scope of scanning is more determined by sectors of the task environment than by those of the general environment. Within the sectors of task environment data about potential clients and competitors is perceived to be most useful. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

3.1.1.3 Degree of Delegation

Information about the Indicators of the Construct 'Degree of Delegation'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.07	1.40
Technologien	0.57	1.24
Wettbewerber	0.46	1.45
Rohstoffe/Zulieferer	0.09	1.21
Politisch/rechtlicher Bereich	0.16	2.34
Wirtschaftliche Rahmenbedingungen	0.19	2.42
Soziokultureller Bereich	0.16	1.91
VIF: Variance Inflation Factor		

Table 38: Information about the Construct 'Degree of Delegation'

Delegation is mostly determined by the delegation of scanning the technological sector and competitors. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

3.1.2 Interpreting

The constructs degree of tool support and fixity of time for interpretation are measured by one indicator. Therefore, an analysis of these constructs in the context of the developed fit criteria is not sensible.

3.1.2.1 Diversity of Internal Models

Information about the Indicators of the Construct 'Diversity of Internal Models'		
Description of Indicators	*Weight*	*VIF*
Mitarbeitern	0.66	1.08
Kunden	0.65	1.44
Zulieferern	0.74	1.54
Geschäftsführern oder Vorständen	0.47	1.08
Unternehmensberatern	0.39	1.19
Anwälten/Steuerberatern	0.40	1.28
Freunden und Familienangehörigen	0.23	1.24
Anderen Personen	0.32	1.22
VIF: Variance Inflation Factor		

Table 39: Information about the Construct 'Diversity of Internal Models'

The construct diversity of internal models is mostly determined by interpretation done together with employees, clients and suppliers. Apart from friends and family all other groups are also important for the interpretation of the data derived from the process of scanning. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

3.1.2.2 Intensity of Interpretation

Information about the Indicators of the Construct 'Intensity of Interpretation'			
Description of Indicators		*Indicator Reliability*	*Item-to-Total Correlation*
Die Interpretation von Informationen über mögliche Chancen und Risiken für mein Unternehmen erachte ich als sehr wichtig.		0.91	-*
Informationen über mögliche Chancen und Risiken für mein Unternehmen interpretiere ich …(1 = nie, 7 = täglich)		0.88	-*
Information about the Construct 'Intensity of Interpretation'			
Internal Consistency	0.89	Average Explained Variance	0.81
**: Calculation not Possible*			

Table 40: Information about the Construct 'Intensity of Interpretation'

Intensity of interpretation is measured by two indicators. Due to this fact no item-to-total correlation is calculated. The indicator reliability, the internal consistency and the average explained variance of the construct are satisfactory. Also, the problem of multidiscriminancy does not exist. All squared correlations between the construct intensity of interpretation and all other latent variables are lower than the average explained variance of the construct.

3.2 Contingency Variables

3.2.1 Environmental Uncertainty

Perceived strategic uncertainty is reflected by three dimensions, i.e. environmental complexity, environmental rate of change and environmental importance.[756]

Environmental Complexity

Information about the Indicators of the Construct 'Environmental Complexity'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.55	1.26
Technologien	0.49	1.23
Wettbewerber	0.08	1.47
Rohstoffe/Zulieferer	0.23	1.24
Politisch/rechtlicher Bereich	0.21	1.23
Wirtschaftliche Rahmenbedingungen	0.04	1.37
Soziokultureller Bereich	0.09	1.30
VIF: Variance Inflation Factor		

Table 41: Information about the Construct 'Environmental Complexity'

Environmental complexity is mostly determined by clients and technologies. The general economic conditions do not contribute to a high extent to environmental complexity. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

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[756] See formula 1.

Environmental Rate of Change

Information about the Indicators of the Construct 'Environmental Rate of Change'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.24	1.41
Technologien	0.36	1.50
Wettbewerber	0.30	1.48
Rohstoffe/Zulieferer	0.28	1.29
Politisch/rechtlicher Bereich	0.01	1.50
Wirtschaftliche Rahmenbedingungen	0.21	1.50
Soziokultureller Bereich	0.41	1.55
VIF: Variance Inflation Factor		

Table 42: Information about the Construct 'Environmental Rate of Change'

The rate of change is influenced by all sectors of the task environment. Apart from the socio-cultural sector the general environment has only a minor influence on the environmental rate of change. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

Environmental Importance

Information about the Indicators of the Construct 'Environmental Importance'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.70	1.13
Technologien	0.60	1.16
Wettbewerber	0.50	1.16
Rohstoffe/Zulieferer	0.28	1.19
Politisch/rechtlicher Bereich	0.00	1.54
Wirtschaftliche Rahmenbedingungen	0.17	1.43
Soziokultureller Bereich	0.18	1.38
VIF: Variance Inflation Factor		

Table 43: Information about the Construct 'Environmental Importance'

This dimension of perceived strategic uncertainty is mainly determined by clients, technologies and competitors. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

3.2.2 Personality

3.2.2.1 Locus of Control

Information about the Indicators of the Construct 'Locus of Control'		
Description of Indicators	*Indicator Reliability*	*Item-to-Total Correlation*
Ich übernehme gerne Verantwortung.	0.61	0.41
Es hat sich für mich als gut erwiesen, selbst Entscheidungen zu treffen, anstatt mich auf das Schicksal zu verlassen.	0.75	0.46
Bei Problemen und Widerständen finde ich in der Regel Mittel und Wege, um mich durchzusetzen.	0.75	0.48
Erfolg ist oft mehr von Leistung, als von Glück abhängig.	eliminated	
Ich habe häufig das Gefühl, dass ich viel Einfluss darauf habe, was mit mir geschieht.	0.63	0.48
Bei wichtigen Entscheidungen orientiere ich mich selten am Verhalten anderer.	eliminated	

Information about the Construct 'Locus of Control'			
Internal Consistency	0.79	Average Explained Variance	0.61

Table 44: Information about the Construct 'Locus of Control'

As indicators with an indicator reliability lower than 0.4 have to be eliminated, items 4 and 6 had to be omitted because of an indictor reliability of 0.32 and 0.31. As a consequence of this elimination the internal consistency of the construct went up from 0.68 to 0.79. The criterion for discriminance validity of the construct is fulfilled because no squared correlation between this construct and any other latent variable is higher than the average explained variance of the construct (0.61).

3.2.2.2 Tolerance for Ambiguity

Information about the Indicators of the Construct 'Tolerance for Ambiguity'		
Description of Indicators	*Indicator Reliability*	*Item-to-Total Correlation*
Ich mag es, wenn Überraschungen auftreten.	0.69	0.60
Ich beschäftige mich gerne mit scheinbar unlösbaren Aufgaben.	0.73	0.47
Ich probiere gerne Dinge aus, auch wenn nicht immer etwas dabei herauskommt.	0.70	0.52
Ich lasse die Dinge gerne auf mich zukommen.	eliminated	
Ich habe es nicht gerne, wenn die Arbeit gleichmäßig verläuft.	0.63	0.47
Ich warte geradezu darauf, dass etwas Aufregendes passiert.	0.65	0.60
Wenn um mich herum alles drunter und drüber geht, fühle ich mich so richtig wohl.	0.71	0.58
Ich muss nicht wissen, was auf mich zukommt.	0.43	0.43

Information about the Construct 'Tolerance for Ambiguity'			
Internal Consistency	0.82	Average Explained Variance	0.62

Table 45: Information about the Construct 'Tolerance for Ambiguity'

The fourth item is eliminated because its internal reliability is 0.21. As the internal consistency is above the minimum level, the item-to-total correlations of the indicators do not have to be considered. The average explained variance of 0.62 is higher than the squared correlations between the construct tolerance for ambiguity and all other latent variables. Therefore, the problem of multidiscriminancy does not exist.

3.2.2.3 Need for Achievement

Information about the Indicators of the Construct 'Need for Achievement'		
Description of Indicators	*Indicator Reliability*	*Item-to-Total Correlation*
Ich halte es für wichtig, mehr zu leisten als andere.	0.69	0.51
Mir scheint es erstrebenswert, in der Gesellschaft weiter zu kommen.	0.69	0.38
Ich stelle große Anforderungen an meine Arbeit.	0.73	0.56
Andere finden, dass ich hart arbeite.	0.70	0.38
Meistens habe ich viel zu tun.	0.63	0.54
Nachdem ich eine schwierige Arbeit begonnen habe, fällt es mir schwer, diese zu unterbrechen.	0.65	0.35
Wenn ich ein selbst gestecktes Ziel nicht erreicht habe, setze ich alles daran, es doch noch zu schaffen.	0.71	0.46
Durchhaltevermögen ist eine wichtige Eigenschaft.	0.43	0.47

Information about the Construct 'Need for Achievement'			
Internal Consistency	0.89	Average Explained Variance	0.61

Table 46: Information the Construct 'Need for Achievement'

The eighth indicator has the very low indicator reliability of 0.43. As the value of internal consistency is very high (0.89), this indicator does not have to be eliminated. The problem of multidiscriminancy does not exist because the average explained variance of the construct is higher than the squared correlations between this construct and all other latent variables.

3.2.2.4 Risk Propensity

<table>
<tr><td colspan="4">Information about the Indicators of the Construct ‘Risk Propensity’</td></tr>
<tr><td colspan="2">Description of Indicators</td><td>Indicator Reliability</td><td>Item-to-Total Correlation</td></tr>
<tr><td colspan="2">Manchmal riskiere ich etwas, nur um Spaß zu haben.</td><td>0.86</td><td>0.72</td></tr>
<tr><td colspan="2">Hin und wieder setzte ich mich Risiken aus, um mich herauszufordern.</td><td>0.88</td><td>0.70</td></tr>
<tr><td colspan="2">Ich finde es manchmal aufregend, Sachen zu machen, für die ich Schwierigkeiten bekommen könnte.</td><td>0.85</td><td>0.71</td></tr>
<tr><td colspan="2">Aufregung und Abenteuer sind für mich wichtiger als Sicherheit.</td><td>0.72</td><td>0.66</td></tr>
<tr><td colspan="4">Information about the Construct ‘Risk Propensity’</td></tr>
<tr><td>Internal Consistency</td><td>0.90</td><td>Average Explained Variance</td><td>0.68</td></tr>
</table>

Table 47: Information about the Construct ‘Risk Propensity’

The reliability of each single indicator is very high. Therefore, no indicator has to be eliminated. Also the internal consistency of the construct is well above the minimum level (0.90). The problem of multidiscriminancy does not exist because the average explained variance of the construct is higher than the squared correlations between this construct and other latent variables.

3.2.2.5 Egalitarianism

Information about the Indicators of the Construct 'Egalitarianism'		
Description of Indicators	*Indicator Reliability*	*Item-to-Total Correlation*
Es ist gerecht, dass nicht alle Menschen gleich viel verdienen und ein gleich hohes Vermögen besitzen.	0.41	0.49
Bei Chancengleichheit ist es gerecht, dass einige Menschen bei höherer Leistung mehr Einkommen erzielen.	0.82	0.53
Es ist gerecht, dass man das, was man sich durch Arbeit verdient hat, behält, auch wenn das heißt, dass einige Menschen vermögender sind als andere.	0.61	0.53
Es ist gerecht, dass Menschen, die viel leisten, mehr verdienen als andere.	0.86	0.51
Es ist gerecht, dass Eltern ihr Vermögen an ihre Kinder weitergeben.	0.52	0.39
Einige Menschen sind begabter und intelligenter als andere. Es ist gerecht, dass es dadurch für sie einfacher ist, ein höheres Einkommen zu erzielen.	eliminated	

Information about the Construct 'Egalitarianism'			
Internal Consistency	0.76	Average Explained Variance	0.62

Table 48: Information about the Construct 'Egalitarianism'

The sixth item is eliminated due to an indicator reliability of 0.28. The resulting value of internal consistency of 0.76 is very high so that no additional indicator has to be eliminated. The problem of multidiscriminancy does not exist because the average explained variance of the construct is higher than the squared correlations between this construct and all other latent variables.

3.2.2.6 Moral Reasoning

Information about the Indicators of the Construct 'Moral Reasoning'		
Description of Indicators	*Indicator Reliability*	*Item-to-Total Correlation*
Versprechen gegenüber einem Freund halten	0.77	0.60
Versprechen gegenüber jemandem einhalten, den man kaum kennt	0.68	0.53
Die Wahrheit sagen	0.52	0.42
Einem Fremden das Leben retten	0.76	0.59
Einem Freund das Leben retten	0.69	0.50
Dinge, die anderen gehören, nicht wegnehmen	0.74	0.57
Sich an Gesetze halten	0.55	0.49
Bestrafung bei Gesetzesbruch	0.56	0.49

Information about the Construct 'Moral Reasoning'			
Internal Consistency	0.86	Average Explained Variance	0.57

Table 49: Information about the Construct 'Moral Reasoning'

The reliability of the indicators is higher than the required minimum level of 0.4. As the internal consistency is 0.86 no indicators have to be eliminated. The problem of multidiscriminancy does not exist because the squared correlations between this construct and all other latent variables are lower than the average explained variance.

3.2.2.7 Machiavellianism

Information about the Indicators of the Construct 'Machiavellianism'		
Description of Indicators	Indicator Reliability	Item-to-Total Correlation
Man sollte nur dann den wahren Grund seiner Handlungen sagen, wenn es einem nutzt.	0.57	0.57
Am sichersten fährt man mit der Annahme, dass alle Menschen auch einen bösartigen Zug haben.	0.44	0.50
Mit Aufrichtigkeit kommt man nicht immer weiter.	0.47	0.49
Bedeutend und unredlich zu sein, ist alles in allem besser als unbedeutend und ehrlich zu sein.	eliminated	
Man soll seine Bekanntschaften auch unter dem Gesichtspunkt auswählen, ob sie einem nützen können.	eliminated	
Meistens ist es günstiger, seine wahren Absichten für sich zu behalten.	0.92	0.61
Wenn man jemanden um etwas bittet, kann man falsche Gründe vorschieben, von denen man sich Erfolg verspricht.	0.56	0.46
Ein weit gestecktes Ziel kann man nur erreichen, wenn man sich auch etwas außerhalb des Erlaubten bewegt.	0.52	0.39

Information about the Construct 'Machiavellianism'			
Internal Consistency	0.71	Average Explained Variance	0.81

Table 50: Information about the Construct 'Machiavellianism'

Items four and five have to be eliminated because the values of the indicator reliability are below the required minimum level of 0.4. They are 0.15 and 0.16. The resulting internal consistency is satisfying. Therefore, no more indicators have to be eliminated. The multi discriminance problem does not exist because the squared correlations between this construct with all other latent variables are lower than the average explained variance.

3.2.2.8 Trust in People

Information about the Indicators of the Construct 'Trust in People'		
Description of Indicators	*Indicator Reliability*	*Item-to-Total Correlation*
Man kann nicht vorsichtig genug sein im Umgang mit anderen Menschen.	0.56	0.46
Die meisten Leute streben eher nach ihrem eigenen Vorteil.	0.82	0.54
Wenn man nicht Acht gibt, werden andere Leute einen ausnutzen.	0.70	0.60
Niemand kümmert sich um einen, wenn es einem schlecht geht.	0.72	0.44
Menschen sind grundsätzlich unkooperativ.	0.56	0.42

Information about the Construct 'Trust in People'			
Internal Consistency	0.81	Average Explained Variance	0.53

Table 51: Information about the Construct 'Trust in People'

All items are reversed items. The internal consistency is high and all indicators are reliable. Due to a high value of internal consistency, no indicator has to be eliminated. The average explained variance is higher than all squared correlations between this construct and all other latent variables. Therefore, the problem of multidiscriminancy does not exist.

3.3 Success Measures

3.3.1 Success of Early Warning

Information about the Indicators of the Construct 'Success of Early Warning'		
Description of Indicators	*Weight*	*VIF*
Kunden	0.46	1.26
Technologien	0.42	1.19
Wettbewerber	0.38	1.23
Rohstoffe/Zulieferer	0.23	1.14
Politisch/rechtlicher Bereich	0.13	1.98
Wirtschaftliche Rahmenbedingungen	0.11	2.18
Soziokultureller Bereich	0.09	1.56
VIF: Variance Inflation Factor		

Table 52: Information about the Construct 'Success of Early Warning'

The construct success of early warning is mainly determined by the sectors clients, technology and competitors. As the values of the variance inflation factor for each indicator are far below 10, the problem of multicollinearity does not exist.

3.3.2 Economic Success

Information about the Indicators of the Construct 'Economic Success'		
Description of Indicators	*Weight*	*VIF*
Umsatzrendite (Betriebsergebnis vor Steuern/Umsatz)	0.80	-
Steigerung des Unternehmenswertes	0.30	-
VIF: Variance Inflation Factor		

Table 53: Information about the Construct 'Economic Success'

The construct economic success is mainly determined by the indicator profit on sales. A multicollinearity problem cannot exist because the construct comprises only two indicators.

4 Cluster Analysis

The objective of cluster analysis is to sort cases (e.g. people) into groups or clusters so that the degree of association between members of the same cluster is greater than the degree of association to members of other clusters.[757] In the context of this work this explorative method is used to sort different types of CEOs in groups according to their attitudes relevant within the context of early warning. Then, early warning behavior and its success will be analyzed for each cluster of CEOs.

These Clusters are the result of a process of three steps.[758] 1) The bases of the process are the collected data.[759] In the here shown case this data comprises the data of CEOs and their attitudes. The difference between each attribute (attitudes) is determined for couples of examined objects (CEOs) by means of a proximity measure. 2) A fusion algorithm (e.g. single-linkage, ward algorithm or complete-linkage) is selected and the analyzed objects are grouped according to the proximity value, so that within each group there are only objects with similar characteristics. 3) Finally, the number of groups is determined.

757 "Eine Menge von Objekten, die durch die Ausprägungen einer Anzahl von Merkmalen charakterisiert werden, soll so in Klassen zerlegt werden, daß die zu einer Klasse gehörigen Objekte möglichst ähnlich und die Klassen untereinander möglichst unähnlich sind." Bergs (1981), p. 4. See also Bock (1974), p. 13 and Vogel (1975), p. 1.

758 See Backhaus, Erichson, Plinke and Weiber (2005), p. 479ff., Bortz and Döring (2003), 382f. and Bergs (1981), p. 23ff.

759 For problems regarding the selection and preparation of data see Bergs (1981), p. 51ff.

Distance measures are applied in the first step.[760] They measure the dissimilarity between objects by comparing all attributes. The selection of an appropriate distance measure depends on the chosen scale of the variables. In the case of interval scaled variables the MINKOWSKI metrics is applied.[761]

$$d_{ij} = \left(\sum_{t=0}^{T} \left| x_{it} - x_{jt} \right|^{k} \right)^{\frac{1}{k}}$$

with d_{ij}: *distance between objects i and j*
x_{it}: *attribute t of object i*
x_{jt}: *attribute t of object j*
k: *MINKOWSKI's constant*

Formula 12: MINKOWSKI's Distance Measure

The second step of cluster analysis is the selection of a fusion algorithm.[762] It is selected according to the two possible modes of clustering: partitional and hierarchical clustering.[763] Partitional clustering methods start with assigning each object to groups. Then, these single objects are exchanged between the groups until the optimal partition is found.[764] Hierarchical clustering can apply two methods – the agglomerative and divisive one.[765] Agglomerative algorithms consider each object of analysis as one single group and agglomerate step-wise; the divisive method takes the opposite direction and first considers all objects as one group and then divides them into more groups.

This study follows BACKHAUS et al. who propose the use of single-linkage and the ward algorithm for clustering large number of objects with attributes that are measured by interval scaled variables.[766] Both algorithms are agglomerative. First, the single-linkage method identifies objects with especially great distance to all others. These objects are then eliminated for further analysis. After that, the ward algorithm is

[760] See ibid., p. 63ff. These distance measures are also called dissimilarity measures. See Everitt, Landau and Leese (2001), p. 41.
[761] See Ibid., p. 40, Chakrapani (2004), p. 61 and Borg and Groenen (2005), p. 90.
[762] See Everitt, Landau and Leese (2001), p. 99 and Hartigan (1975).
[763] See Jain and Dubes (1988).
[764] See Guha, Rastogi and Shim (2004), p. 45.
[765] See Johnson (1967) and Hubert and Schultz (1975).
[766] See Backhaus, Erichson, Plinke and Weiber (2005), p. 516f. and Kohn (2005), p. 551.

applied which is the algorithm mostly used in the context of obtaining groups of objects.[767]

The final step of cluster analysis is to determine the number of groups. As the chosen agglomerative procedures reduce the number of groups from the number of all possible groups to one final group, an additional method has be applied to determine the optimal number of clusters. It should be determined on the basis of statistical reasons and not in respect to content. Therefore, the elbow criterion is applied which will be described in the following.768 According to it, the number of clusters should be reduced until the sum of squared measurement errors augments in a disproportionate way. For a graphical representation the sums of squared measurement errors are depicted in dependency of the amount of groups and the amount of groups is optimal at the determined kink.769 The sum of squared measurement errors is determined by the following formula:

$$V_g = \sum_{k=1}^{K_g} \sum_{j=1}^{J} \left(x_{kjg} - \overline{x}_{jg} \right)^2$$

with	V_g:	*sum of squared measurement errors of group g*
	K:	*analyzed objects in group g*
	J:	*attributes*
	x_{kjg}:	*value of attribute j of analyzed object k in group g*
	$\overline{x}_{kjg}$:	*mean of attribute j in group g*

Formula 13: Sum of Squared Measurement Errors

[767] See Bergs (1981), p. 96f. and Punj and Stewart (1983), p. 137ff. For its advantages see Breckenridge (1989), p. 150ff. and Edelbrock (1979), p. 371ff.

[768] See Everitt, Landau and Leese (2001), p. 102 and Backhaus, Erichson, Plinke and Weiber (2005), p. 511.

[769] See G 2.4.3.