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Chapter 5

Evaluating and Adapting the Autonomy Construct

This chapter attempts to answer *RQ2: How can the autonomy dimensions identified by RQ1 be operationalized in a construct that enables us to measure the autonomy of venture managers?* For this task, the validity and the reliability of the initial multidimensional autonomy construct, presented in Chapter 4, are statistically evaluated and adapted. The resultant construct is the answer to RQ2. The chapter proceeds as follows. Section 5.1 presents the data set that is used to evaluate the initial autonomy construct. The procedure described by Field (2013) is followed in Section 5.2 in order to evaluate the validity and the reliability of the autonomy construct. The results of the chapter are summarized in Section 5.3. There the answer to RQ2 is formulated.

Parts of this chapter are based on the following publication[3]:

Gard, J., Baltes, G., Andersen, T. J., & Katzy, B. (Forthcoming 2016). **Corporate venture management in small-medium sized enterprise: The roles and effects of autonomy and corporate policy**. In the Journal of Business Venturing.

[3] The author would like to thank his co-authors and the publishers of the Journal of Business Venturing for their permission to reuse relevant parts of the articles in this thesis.

5.1 DATA SET USED TO EVALUATE THE AUTONOMY CONSTRUCT

The data set used to evaluate the validity and the reliability of the initial autonomy construct (provided in Chapter 4) is presented in this section. The section proceeds as follows. The Subsection 5.1.1 reports on the sample framing. The Subsection 5.1.2 describes the data collection. The Subsection 5.1.3 reports on the identification of the target population in the collected sample.

5.1.1 SAMPLE FRAMING

Corporate ventures are in contrast to independent ventures (i.e., start-ups) not visible from the outside. There is nothing like an ultimate source that would enable one to identify venture teams of corporations. So, the first action is already critical for the sample framing, viz. to identify corporations that are engaged in corporate venturing. The German IT consulting industry is recognized as an adequate industry for collecting corporate venture-related data (Fincham, 2006). The industry is facing continuous technological development and market change. Corporations competing in such an innovation-driven industry are required to renew continuously their businesses in order to establish long-time survival and profitability. Thus, the rate of corporate venture initiatives is expected to be rather high.

Database used to collect firm information

Firm information is gathered via the Hoppenstedt firm database[4]. More than 850,000 firms are listed and information, such as address, contact details, legal forms, NACE codes, size in number of employees and annual sales, names and positions of top and middle management, is available in the database (NACE is the European industry standard classification system; it

[4] http://www.hoppenstedt-firmendatenbank.de/

means Nomenclature Générale des Activités Économiques dans les Communautés Européennes). With respect to the sample framing, the Hoppenstedt database is chosen to identify small-size to medium-size IT consulting firms in Germany and to gather information concerning managers that are potentially involved in corporate venture initiatives.

Gathering information on the target firms

Data collection is restricted to SMEs for the reasons given in Subsection 1.3.4. According to the classification of the European Commission (Commission, 2003), a firm size between 30 to 400 employees and a turnover above 4 million Euro are chosen as selection criteria. SMEs in the German IT-industry are identified through NACE codes. The codes are captured by using secondary databases provided by Oracle, Microsoft and SAP. The secondary databases contain IT consulting firms that are certified distribution partners and implementation partners of the three global players. The analysis of the databases reveals that IT consulting firms can be identified by the following 5-digit NACE codes: 72100, 72221, 72223, 72305, 72602 and 74141. According to the German Classification of Economic Activities (WZ2003), the NACE codes have the following meanings: hardware consultancy (72100), software consultancy (72221), other software development (72223), other data processing (72223), other computer related activities n.e.c. (72602) as well as business and management consulting activities (74141).

14451 corporations are identified in the Hoppenstedt database using the five identified NACE codes as selection criteria. 11495 of these firms are classified as micro firm (<30 employees) and 184 as large firms (>400 employees). The remaining 2772 (14451-11495-184) are identified as SMEs and retained for the study. Firm profiles are checked online and firms excluded when related to other industries. In total, 2649 German IT consulting firms remained and are identified in the database as SMEs.

The target population

The target population are the managers of the 2649 firms that are involved in corporate venture management. However, there is no ultimate source that would clearly identify those managers. In fact, every top- and middle manager might or might have been involved in corporate venture management. In order to create a comprehensive list of potentially involved managers, the researcher and his support staff went through the Hoppenstedt firm database and extracted the names and email addresses of the top- and middle managers. In the 2649 firms, the names and email addresses of 15420 managers could be extracted from the Hoppenstedt database. All email addresses were checked by the support staff using google as a search engine, whereby only those email addresses were recorded that were found via google search. Overall, 14850 (of the 15420) email addresses were found, thus evaluated.

As a result of our sample framing approach based on available information in the Hoppenstedt database in combination with google search, the resulting sample population of 14850 (the collected sample) may differ fundamentally from the target population. The difference is the result of an over-coverage of the target population. It can be expected that not all managers in the sample are/were involved in corporate venture management. The reason is that the Hoppenstedt database does not provide the exact job description so that for example project managers or assistants may be included in the sample. Thus, not all people in the sample population are part of the target population. In the following, the data collection is described before the method applied to extract the target population from the sample population is described in Subsection 5.1.3.

5.1.2 DATA COLLECTION

Data is collected via an online survey, using the web 2.0-based software Qualtrics. The data collection was started on November 5, 2012 and ended on January 10, 2013. Using the email template given in Appendix D1, the 14850 managers were invited via email to participate in the study. Following the web link provided in the email, participants were directed automatically to the starting page of the online survey (see Appendix D2). By entering the access code, which was also provided in the email, they could start the survey.

Overall, 2322 emails could not be delivered and were returned to the sender, primarily with the message that the email address did not exist. It was checked whether (a) the email addresses were outdated or (b) a mistake was made in the collection of email addresses or the sending of email. In fact, all email addresses could be found via google. A sample of 100 email addresses were cross-checked by searching on the homepage of the respective company whether the email addresses could be found. It was found that the email addresses were outdated as they could primarily not be found on the companies' homepages.

Although a certain number of email were invalid, the collection and the email sending was sound and 12528 emails reached their addressees. In total, 607 responses were received during the data collection period. These responses refer to fully completed surveys only. As invitations to the online survey where sent to several managers in the same firm, it is not surprising that several answers were received from the same firm. The 607 responses were received from 473 distinct firms. In addition to the fully completed surveys, 553 partially completed surveys were received. They are however not considered as relevant for this thesis and excluded from data analysis.

Particular care was taken to ensure that the respondents refer their answers to corporate ventures. Therefore, the following four steps are taken. *First*, a cover letter is provided to each participant on the start page of the online survey (see Appendix D2). The cover letter explains the aim of the study and gives a definition of the term corporate venture. *Second*, the first part of the survey is a Screener that includes (a) a question to identify whether participants are currently involved in corporate venturing or (b) participants were involved in corporate venturing in the past (see the questions 3 and 4 in Appendix E2.1). Depending on their answers given, the questions of the survey are formulated in present of past tense. Those participants who had not experience with corporate ventures were directed to a different survey, which is not part of this study. *Third*, those participants with corporate venture experience are requested to make reference to a specific corporate venture team when responding to the survey. *Fourth*, the participants are asked to state their role in the corporation with respect to the relation they have with corporate ventures (see the question 8 in Appendix E2.1).

Although, particular care was taken to ensure that participants refer their answers to corporate ventures, it is expected that not all of them are part of the target population. Therefore, the following approach is applied to identify the target population in the collected sample.

5.1.3 IDENTIFICATION OF THE TARGET POPULATION IN THE COLLECTED SAMPLE

Three questions are included in the first part of the survey (Screener) that enable us to identify the target population in the collected data.

The first question (see the questions 1 in Appendix E2.1) aims to identify participants in a management position. Therefore, respondents are asked to state their current position in the company. Possible answers are, (1) Board of Directors, (2) Executive Board, (3) Chief Executive, (4) Head of the Business Development Department, (5) Head of another Department, (6) Project Manager/ Team Leader, (7) Employee and (8) another position. Only responses of participants in a management position (1-6) are considered.

In a second question (see the questions 3 in Appendix E2.1), participants need to state whether there is a team in their company that currently develops a new business, or did so during the past 3 years. Possible answers are, (1) yes, there are one or more teams that are currently developing a new business; (2) yes, we had one or more teams that developed a new business in the past 3 years; (3) no, there are no such teams in our company. Responses are only considered when the answer is: yes, there are one or more teams that are currently developing a new business.

A third question (see the questions 8 in Appendix E2.1) identifies the relation that participants have with corporate ventures. Participants are asked to state which of the statements applies to them personally. Possible answers are: (1) I am currently the leader of a team that has the task to develop a new business; (2) I am currently the leader of a team that already has developed a new business in the past 3 years, (3) I am currently the supervisor of the leader of a team that currently develops a new business, (4) I am the supervisor of the leader of a team that already developed a new business in the past 3 years, (5) I am currently member of a team that currently develops a new business or that already did so in the past 3 years. (6) I have currently no relation with a team that develops a new business. However, I have made some experience in the past. (7) I have never made any experience with a team that develops a new business. Based on the respective answer, participants are differentiated in the seven respondent groups given in Table 5.1.

Table 5.1: Respondent Groups in the Sample Frame

Respondent Group	
1 Venture manager currently involved in new business development	**87**
2 Venture manager with past involvement in new business development	53
3 Corporate manager currently supervising the venture manager	297
4 Corporate manager supervising the venture manager in the past	43
5 Employee of a corporate venture team	62
6 Respondent who had a relation with a corporate venture in the past	34
7 Respondent who has no experience with corporate venturing	31

Responses (606) are received from all of the four respondent groups highlighted in Table 5.1. Ad (1), 87 participants are venture managers that are currently responsible for new business development. Ad (2), 53 responses are received from venture managers that were responsible for new business development in the past. Ad (3), 297 respondents are corporate managers that are currently supervising venture managers. Ad (4), 43 responses refer to corporate managers that were responsible for corporate ventures in the past. Ad (5), 62 participants are/were employees (not in a management position) of a corporate venture team. Ad (6), 34 answers are given by participants that had a relation with corporate ventures in the past. Ad (7), 31 participants have no experience with new business development through corporate ventures.

Only the responses of group 1 (venture manager currently involved in new business development) are considered for data analysis in this thesis. The three reasons for this choice are given in the following.

Judgment on the responses used for data analysis

The first reason refers to the target population that is defined in Subsection 5.1.1. It is expected that only those respondents in a management position provide valid information on corporate venture management and are thus relevant for data analysis. It can be expected that at least some of the respondents of group 5 (employees of corporate venture) and group 7 (respondents with no experience with corporate venturing) are or were not in a management position. Their answers are consequently excluded from data analysis.

The second reason refers to the general method validity. Data that managers provide on past experience may be subject to incorrect information due to loss of memory and re-interpretation, which is known as hindsight bias. In order to eliminate the possibility that data analysis is constrained through hindsight bias, the answers of the group 2 (venture manager with past involvement in new business development), group 4 (corporate manager supervising the venture manager in the past) and group 6 (respondent who had a relation with a corporate venture in the past) are not considered for data analysis. These participants were involved in corporate venturing in the past.

The third reason draws on the experiences made during the interviews (see Chapter 3). In the interviews (see Appendix A) it was observed that corporate managers may provided incorrect information on the autonomy that venture managers enjoy. For example, one corporate manager stated that the venture manager was granted with high strategic autonomy. However, subsequent interviews showed that the corporate manager made most strategic decisions himself and guided the strategic direction of the corporate venture, even without the participation of the venture manager. Such biased perception of corporate managers are also found in previous studies (see, e.g., Glaister, Husan, & Buckley, 2003).

In order to test our observation statistically, we conducted an analysis of variance (ANOVA) in order to compare the assessment of autonomy among the corporate managers and the venture managers. Our results confirm that the assessment is significantly different. Venture managers assess strategic autonomy with 18.32 (s.d.=5.69) and job autonomy with 33.25 (s.d.=5.77). Corporate managers assess strategic autonomy with 14.68 (s.d.= 5.91) and job autonomy with 31.11 (s.d.= 5.74). The results of the ANOVA given in the Appendix J2 and the Appendix J3 show that the differences are significant ($p<.00$). Thus, the corporate managers assess autonomy on average lower than the venture managers. The results confirm our observation (made during the interviews) that corporate managers have the potential to generate biased results with respect to the assessment of the autonomy that venture managers enjoy. In order to avoid that data analysis is constrained through the biased perception of the corporate manager, the responses of group 3 (corporate manager currently supervising the venture manager) are not considered for data analysis.

For the three reasons given above, only those 87 responses of the venture managers that are currently involved in new business development are considered as valid for data analysis. Compared to the targeted sample of 2649 firm, our final response rate of 3.3% is not uncommon in empirical studies with our target group of middle managers (cf. Lepak, Takeuchi, & Snell, 2003; Ozgen & Baron, 2007). The average size of the firms was 279.11 (SD=691.85) full-time employees whereas one firm had less than 30 employees and five firms had more than 400 employees. The average team size of the corporate venture was 9.55 (SD=15.14) full-time employees. A list of the corporations from which the responses were received is provided in the Appendix C. The data set of the 87 venture managers is applied in Section 5.2 in order to evaluate the autonomy construct that was operationalized in Chapter 4.

Remarks on the sample size

The author of this thesis is aware that we live today in an age of big data and a sample size of 87 is not acceptable in research domains where terabytes and petabytes of data are available. However, big data that would allow to analyze corporate venture management is not available to the author's best knowledge. As it is later discussed in the limitations of the thesis (see Section 7.4), a sample size of 87 was the research standard in corporate venture scholars when the data was collected for this thesis in 2012. In order to inform the reader, the sample size of the most recent studies are given in the following: Johnson (2012) with a sample size of n=64, Crockett et al. (2013) with a sample size of n=78, Thornhill and Amit (2000) with a sample size of n=102, Birkinshaw and Hill (2005) with a sample size of n=95 and Garrett and Covin (2013), Garrett and Neubaum (2013) as well as Kuratko et al. (2009) with a sample size of n=145. Thus, studies with a sample size that would fulfill the criteria of big data are not available in the research domain of this thesis.

5.2 CONSTRUCT VALIDITY AND CONSTRUCT RELIABILITY

The validity and the reliability of the autonomy construct developed in Chapter 4 are evaluated following the procedure described by Field (2010). The procedure includes the four steps (1) evaluating the appropriateness of the data set to apply variable reduction techniques, (2) component extraction, (3) component rotation and (4) computation of Cronbach's Alphas. The construct validity is evaluated in the first three steps which are reported in the Subsections 5.2.1 to 5.2.3. The construct reliability is evaluated in the fourth step which is reported in the Subsection 5.2.4. The results of the validity and reliability analyses are summarized in the Subsection 5.2.5.

Table 5.2 shows how the items (questions) are distributed over the measurement scales (autonomy dimensions). A detailed overview of the items is given in the Appendix E.

Table 5.2: List of Items Referring to the Four Autonomy Scales

Measurement Scale (Autonomy Dimension)	Questionnaire Items
Job Autonomy	1-7
Strategic Autonomy	8-13
Decision Autonomy	14-21
Functional Autonomy	22-29

5.2.1 EVALUATING THE APPROPRIATENESS OF THE DATA

In the *first step,* it is tested whether the data is appropriate to apply variable reduction techniques (e.g., principal factor analysis and principal component analysis).

Definition 5.1: **Variable Reduction Techniques** "*are multivariate statistical procedures to determine the number of variables that account for the variation and covariation among a set of observed measures" (Brown, 2015).*

The following three criteria are checked to evaluate whether the data is appropriate to perform variable reduction techniques: (1) the correlation matrix, (2) the Kaiser-Meyer-Olkin index (KMO) and (3) the Bartlett's test of sphericity. The three criteria are defined below.

Definition 5.2: **Correlation Matrix** "*is a matrix giving the correlations between all items. The correlation is a standardized measure of the strength of a relationship between two items on a scale from -1 to +1" (cf. Field, 2013).*

Definition 5.3: **Kaiser-Meyer-Olkin** "*is an index for comparing the magnitudes of observed correlation coefficients with the magnitude of partial correlation coefficients. The smaller the value of the index, the less appropriate the model" (cf. Henry, 2003).*

Definition 5.4: **Bartlett's Test of Sphericity** *"indicates whether the correlation matrix is an identity matrix, which would indicate that the variable are unrelated. Very small values (less than 0.05) indicate that there are probably significant relationships among the variables" (cf. Sobh, 2008).*

To be considered suitable for variable reduction techniques, the correlation matrix should show (1) at least some correlation coefficients with a value of $r > .3$, (2) the KMO index should show a scores of .60 or higher, (3) the Bartlett's Test of Sphericity should be significant at $p < .05$. The results of the inspections with respect to the three criteria are reported in the following.

- The correlation matrix associating the items reported in Table 5.2 with each other is reported in the Appendix F. The inspection of the correlation matrix shows that 74 coefficients are above the $r \geq .3$ threshold criteria, which indicates that some of the 23 items of functional autonomy, decision autonomy, strategic autonomy and job autonomy are correlated.

- The KMO index was computed to measure the adequacy of the sample. The KMO index is computed with a value of .654, which is above the .60 threshold. Thus, the KMO criteria verifies the sampling adequacy for the analysis.
- The Bartlett's test of sphericity is significant at p<.000, which supports that common component are present in the correlation matrix.

Based on the inspections of the correlation matrix, the KMO index and the Bartlett's test of sphericity, we may conclude that the data is suitable for variable reduction techniques. So, we continue the procedure with the second step.

5.2.2 COMPONENT EXTRACTION

In the *second step*, it is evaluated (a) which variable reduction techniques is suitable to the data set and (b) how many variables should be extracted.

Judgment on the suitable variable reduction technique

Principal Factor Analysis (also known as Principal Axis Factoring) and Principal Component Analysis are the commonly used variable reduction techniques. The Principal Factor Analysis should be applied when the variables (here called factors) are correlated. In contrast, Principal Component Analysis should be performed when the variables (here called components) are correlated with each other. Therefore, the correlations of the variables (i.e., the four autonomy dimensions) are computed in order to assess whether Principal Factor Analysis or Principal Component Analysis is an appropriate technique. The correlation matrix of the four expected variables, namely, functional autonomy, decision autonomy, strategic autonomy and job autonomy is given in Table 5.3. The item operationalization of the four autonomy measures is given in the Appendix E.

Table 5.3: Correlation Matrix of Expected Variables

	Functional Autonomy	Decision Autonomy	Strategic Autonomy	Job Autonomy
Functional Autonomy	1			
Decision Autonomy	.171	1		
Strategic Autonomy	.144	**.420***	1	
Job Autonomy	.007	**.213***	**.462***	1

*. Correlation is significant at level of $p \leq .05$

The correlation matrix (Table 5.3) shows significant correlations between decision autonomy and strategic autonomy (r = .420), between decision autonomy and job autonomy (r = .213) as well as between strategic autonomy and job autonomy (r = .462). Thus, we may conclude that some of the variables (to be extracted) are correlated with each other. Accordingly, Principal Component Analysis is chosen instead of Principal Factor Analysis.

Definition 5.5: **Principal Component Analysis** *"A Principal Component Analysis is a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. It is a multivariate analysis technique for identifying the linear components of a set of variables" (cf. Field, 2013; Pallant, 2013).*

Judgment on the number of variables extracted

The initial Principal Component Analysis is performed (with the 29 items shown in Table 5.2) in order to identify the number of components to extract from the data set. The Principal Component Analysis is based on the computation of Eigenvalues.

Definition 5.6: **Eigenvalues** *"represent the total variance that is explained by each component. The eigenvalue of a given component measures the variance in all the items which is accounted for by that component that can be computed as the sum of its squared component loadings for all the items under a particular component. The eigenvalue explains the relative importance of the component with respect to the items" (cf. Tam, Thomas, & Zhang, 2007).*

The following three criteria on information are inspected to identify the number of components that should be retained for the final Principal Component Analysis:

- (1) Kaiser's criterion
- (2) Point of inflexion in the Scree Plot of Eigenvalues
- (3) Significant Eigenvalues computed by the Parallel Analysis.

The three criteria are defined at the beginning of the discussions of the corresponding observations.

(1) Kaiser's Criterion

Definition 5.7: **Kaiser's Criterion** *"is the rule to drop all components with eigenvalues under 1.0" (cf. Kaiser, 1960).*

The results of the initial Principal Component Analysis allow to obtain the Eigenvalues of the components present in the data. The results show that ten components with an Eigenvalue greater than 1 are present in the data (see Table 5.4, second column), which fulfills the Kaiser's criterion (Kaiser, 1960). The ten components explain 19.87%, 10.79%, 9.41%, 8.32%, 5.49%, 4.73%, 4.33%, 3.93%, 3.56% and 3.49% of variance (see Table 5.4, third column). In total, the components explain a variance of 73.91 %. The components 11 to 29 should be rejected as they show Eigenvalues below 1. The results are summarized in Table 5.4.

Table 5.4: Eigenvalues Extracted through the Initial Principal Component Analysis

Component	Actual eigenvalue from PCA		
	Eigenvalue	% of Variance	Cumulative %
1	**5.763**	**19.873**	**19.873**
2	**3.129**	**10.789**	**30.662**
3	**2.728**	**9.408**	**40.070**
4	**2.412**	**8.319**	**48.389**
5	1.592	5.489	53.878
6	1.371	4.729	58.607
7	1.254	4.325	62.932
8	1.138	3.926	66.858
9	1.031	3.556	70.414
10	1.014	3.496	73.910
11	0.899	3.099	77.008
…			
29	.112	.385	100.000

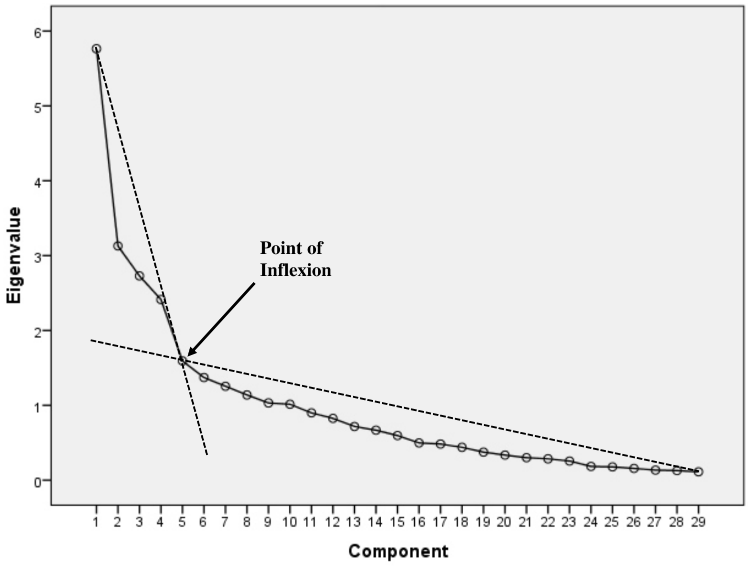
It is acknowledged that the Kaiser's criterion (Eigenvalues greater than 1) is not the most accurate criterion to determine the number of components to be retained in the Principal Component Analysis (cf. O'Connor, 2000). Applying the Kaiser's criterion alone may misguide researchers to extract too many components. The initial results should therefore be compared with the Scree Plot of the extracted Eigenvalues of the component and the results of the Parallel Analysis (cf. Pallant, 2010), which is done in the following.

(2) Scree Plot

Definition 5.8: **Scree Plot** *"is a graph that plotting each eigenvalue (Y-axis) against the components with which it is associated (X-axis). The scree plot indicates the relative importance of each component" (cf. Field, 2013).*

The Scree Plot illustrated in Figure 5.1 is checked for a change in its shape (i.e., elbow), described as the point of inflexion (cf. Field, 2013). The visual inspection indicates that four components should be retained as the components 1, 2, 3 and 4 are above the point of inflexion (illustrated in Figure 5.1). This judgment is however not accurate as it is not determined statistically. Therefore, Parallel Analysis is conducted to determine statistically the number of components that should be retained for the final analysis.

Figure 5.1: Scree Plot of the Component Eigenvalues



(3) Parallel Analysis

Definition 5.9: **Parallel Analysis** *"is a Monte-Carlo-Simulation-based method that allows to determine the number of components to retain in the Principal Component Analysis. The method compares the observed Eigenvalues (raw data) extracted from the correlation matrix to be analyzed with those obtained from uncorrelated normal variables. Parallel Analysis implies a Monte-Carlo simulation process, since 'expected' eigenvalues are obtained by simulating normal random samples that parallel the observed data in terms of sample size and number of variables" (cf. Horn, 1965; Ledesma & Valero-Mora, 2007).*

Parallel analysis is conducted to determine the statistically significant Eigenvalues of the components. Significant Eigenvalues indicate more accurately the number of components to retain for Principal Component Analysis than the Kaiser's criterion (cf. O'Connor, 2000). Research shows that the accurate number of components should be carefully evaluated to differentiate between major and minor components (cf. Fabrigar, Wegener, MacCallum, & Strahan, 1999). Studies comparing different kinds of methods that allow to make informed retaining decisions (see, e.g., Kaiser's criterion, Bartlett's chi-square test, average partial method and parallel analysis) found that parallel analysis produces the most accurate results (cf. Zwick & Velicer, 1986).

Correspondingly, parallel analysis is conducted to determine the number of components. The syntax developed by O'Connor (2000) is therefore used. The full syntax is available online[5] and can be found in the Appendix G. The results of the parallel analysis are presented in Table 5.5.

Table 5.5: Results of the Parallel Analysis

Components	Raw Data	Random Data	Decision
1	**5.404**	**1.841**	**Accept**
2	**2.773**	**1.559**	**Accept**
3	**2.342**	**1.389**	**Accept**
4	**1.989**	**1.247**	**Accept**
5	1.114	1.119	Reject
6	0.999	1.001	Reject
7	0.796	0.900	Reject
8	0.679103	0.809881	Reject
…			Reject
29	-0.271326	-0.400754	Reject

Table 5.5 shows the Eigenvalues extracted from the raw data (column 2) and the Eigenvalues extracted from the random data set at the significance-level of p=.05 (column 3). Correspondingly, Eigenvalues extracted from the raw data set (original data) that exceed the

[5] https://people.ok.ubc.ca/brioconn/nfactors/nfactors.html

significant Eigenvalues of the random data set can be interpreted as meaningful. The results of the parallel analysis show that the Eigenvalues of four components (raw data) exceed the significant Eigenvalues of the random data set. Thus, the results of the parallel analysis provide evidence that the number of components to retain for further analysis should be four.

The four components explain a variance of 19.87%, 10.79%, 9.41%, 8.32% (see Table 5.4, third column). In total the four components explain a variance of 48.38% (see Table 5.4, fourth column). Having evaluated the number of components, the procedure continuous with the component rotation.

5.2.3 COMPONENT ROTATION

In the *third step*, component rotation is conducted. Before component rotation is performed, the correlations between the four components are inspected in order to evaluate whether orthogonal or oblique rotation methods should be used. Orthogonal rotation methods (e.g., Varimax) assume that the components are uncorrelated in the analysis. In contrast, oblique rotation methods assume that the variables are correlated in the analysis. Following the procedure described by Field (2013), Principal Component Analysis is performed with Oblimin as a rotation method in order to compute the component correlation matrix.

Definition 5.10: **Oblimin** *"is a method of oblique rotation that allows the underlying factors to be correlated. The method is used when the researcher wishes a non-orthogonal (oblique) solution" (Field, 2013).*

The results are presented in Table 5.6. The highest correlation coefficient is with a value of $r = .155$ below the threshold criteria ($r > .3$) which shows that the components are uncorrelated (cf. Field, 2013). Thus, we may conclude that orthogonal rotation is the appropriate rotation method.

Table 5.6: Component Correlation Matrix

	Functional Autonomy	Decision Autonomy	Strategic Autonomy	Job Autonomy
Functional Autonomy	1			
Decision Autonomy	.155	1		
Strategic Autonomy	.151	.112	1	
Job Autonomy	-.011	.062	.046	1

Varimax rotation is the most commonly used orthogonal rotation method (cf. Field, 2013) and is therefore chosen to perform the component rotation.

Definition 5.11: **Varimax Rotation** *"is an orthogonal rotation of the component axes to maximize the variance of the squared loadings of a component (column) on all the items (rows) in a component matrix, which has the effect of differentiating the original items by extracted components" (cf. Tam et al., 2007).*

Table 5.7 shows the Varimax rotated solution. The component loadings and the cross-loadings of the items are checked to evaluate the construct validity. Good construct validity is given when the following two criteria are achieved. First, component loadings should be greater than .60. Second, cross-loadings should be below .30. The result of the initial component rotation shows that four items associated with component 1 and five items associated with component 2 show component loadings above .60 and cross-loadings below .30 (highlighted in Table 5.7). In contrast, only two items associated with component 3 and one item associated with component 4 adhere to the threshold criteria. However, at least three items for each component are recommended to perform further data analysis (cf. Field, 2013). Thus, the components 3 and 4 should be rejected. As the components 3 and 4 are mainly loaded through the items of the measurement scales for functional autonomy and decision autonomy (see Table 5.2), it is decided to exclude these two measurement scales in order to improve the results of the component rotation.

Table 5.7: Component Matrix after Initial Component Rotation [a,b]

Item	**Component**			
	1	**2**	**3**	**4**
1	.531			
2	**.743**			
3	**.747**			
4	**.682**			
5	**.612**			
6	.624			.312
7	.570			
8	.383			
9	.403	.434		
10	.478			
11		**.617**		
12		**.606**		
13		.595		
14		**.600**		
15			.478	
16		**.643**		
17		.466	.606	
18			**.680**	
19			.512	
20			**.672**	
21			.544	
22		.361	-.374	.358
23				.460
24		**.638**		
25		.341		
26				**.690**
27				.301
28				.544
29				.418

[a] Varimax rotated component matrix
[b] Table includes all component loadings above the .30 cut-off point

Correspondingly, the component rotation is performed with the items of the two measurement scales strategic autonomy and job autonomy retained. After excluding the items that still did not show component loadings greater than .60 and cross-loadings below .30, the component solution presented in Table 5.8 is found.

Table 5.8: Rotated Component Solution [a,b c]

Item	Component	
	1	2
2	**.800**	
3	**.789**	
4	**.794**	
5	**.695**	
6	**.640**	
7	**.627**	
9		**.681**
11		**.851**
12		**.832**
13		**.787**

[a] Varimax rotated component matrix
[b] Table includes all component loadings above the .30 cut-off point
[c] Results after erasing item 1 for job autonomy and items 1 and 3 for strategic autonomy

The final component rotation confirm the presence of two distinct autonomy measures, namely, strategic autonomy and job autonomy. In order to ensure good construct validity, the items with component loadings below .60 and cross-loadings above .30 were excluded. Consequently, item 1 of component 1 (job autonomy) was excluded for the component rotation. Also, the items 8 and 10 referring to component 2 (strategic autonomy) were exclude. Thus, the original seven-item scale for job autonomy is reduced to a six-item scale and the original six-item scale for strategic autonomy is reduced to a four-item scale. Having validated the component solution, it is continued with the last step in which the reliability of the construct is evaluated. Therefore, Cronbach's Alpha coefficients are calculated for the two remaining components.

5.2.4 CRONBACH'S ALPHA

In *step four*, Cronbach's Alpha coefficients are computed for the two validated components in order to evaluate the reliability of the autonomy construct.

Definition 5.12: **Cronbach's Alpha** *"is a coefficient for measuring the internal consistency of a group of items. The coefficient is useful to understand the extent to which the rating from a group of items hold together to measure a common component" (cf. Cronbach, 1951; Osborne, 2008).*

Cronbach's Alpha (α) can range from a scale of .0 (low internal consistency) to 1.0 (high internal consistency). The interpretation of alpha coefficients is as follows: "$\alpha > .9$ is excellent, $\alpha > .8$ is good, $\alpha > .7$ is acceptable, $\alpha > .6$ is questionable, $\alpha > .5$ is poor, and $\alpha < .5$ is unacceptable" (Gliem & Gliem, 2003). Results show that the Alpha coefficient of the component 2 (strategic autonomy) is α=.81 and the Alpha coefficient of the component 1 (job autonomy) is α=.82. These results show that the autonomy construct has a good internal consistency as the Alpha coefficients are above .8. With this last step, the evaluation of the autonomy construct is completed. The results of the validation and reliability analysis are summarized in the following subsection.

5.2.5 RESULTS OF THE VALIDITY ANALYSIS AND RELIABILITY ANALYSIS

The data analyses reveal a two-dimensional autonomy construct with a good validity and a good reliability. The rotated two-component solution (Table 5.8) shows that the retained items to measure strategic autonomy (items 9, 11, 12 and 13) and job autonomy (items 2, 3, 4, 5, 6 and 7) achieve cross-loadings <.30 and component loadings >.6. Good construct validity is evident as these two threshold criteria are fulfilled. Good construct reliability is confirmed as Cronbach's Alpha coefficients for the strategic autonomy scale and the job autonomy scale are both above .8.

5.3 CHAPTER CONCLUSION

The chapter answers *RQ2: How can the autonomy dimensions identified by RQ1 be operationalized in a construct that enables us to measure the autonomy of venture managers?* Four autonomy dimensions (components) are initially extracted from the data using Principal Components Analysis in combination with Parallel Analysis. However, the results of the component rotation show that the construct validity of the initial four-dimensional autonomy construct (including the items of the four measurement scales, namely, functional autonomy, decision autonomy, strategic autonomy and job autonomy) is problematic. The general threshold criteria that would confirm construct validity are not achieved. The scales of functional autonomy and decision autonomy are removed as most of these scale-items do not load appropriately. The Varimax-rotated two-dimensional autonomy construct (two-component solution), with the scales of strategic autonomy and job autonomy retaining, produces good construct validity. Subsequent reliability analysis shows also good construct reliability of the two-dimensional autonomy construct. Therefore, the original four-dimensional autonomy construct is reduced to a two-dimensional autonomy construct (see Figure 5.2) in order to ensure construct validity and construct reliability. The two-dimensional autonomy construct is applied in the following Chapter 6.

Figure 5.2: The Adapted Autonomy Construct