Business incubators: the impact of their support
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Chapter 5

Validation of the Supportive Activities Construct

In this chapter, we are completing the answer to RQ2.

RQ2: *How can the supportive activities be operationalized in a construct that enables us to measure the impact of the identified supportive activities by UBIs on the performance of an NTBF?*

Chapter 4 successfully answered the first part of RQ2 by (1) developing a theoretical model of the study, (2) identifying the moderating role of the NTBF's capabilities, and (3) exploring how the construct can be operationalized. Following the outcome of Chapter 4, this chapter will complete the answer to RQ2 by (4) statistically evaluating the validity and reliability of the dimensions of the construct. Thus, the resultant construct will be evaluated with respect to the supportive activities by the business incubators through measuring their performances and outcomes.

The chapter proceeds as follows. The characteristics of the employed data set to evaluate the proposed measurement construct is presented in Section 5.1. Section 5.2 describes the method of analysis. Then, Section 5.3 evaluates the validity of the construct. Section 5.4 demonstrates the results of the construct's reliability. After that, Section 5.5 summarizes the results of the validity and reliability analysis of the construct. In Section 5.6, a summary of the answer to RQ2 will be given.

This chapter is based on the following publication:

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5.1 Characteristics of the Employed Data Set

This section reports the characteristics of the employed data set that is used to evaluate the construct and to measure its validity and reliability. It proceeds as follows. Subsection 5.1.1 describes the sampling design. Then, subsection 5.1.2 describes the process of data collection. Lastly, subsection 5.1.3 explains the characteristics of the sample.

Below, we provide a definition of characteristics as used by us in this research.

> **Definition 5.1**: ***Characteristics*** *are defined (in this study) as a combination of criteria on which the selection of the population of NTBFs is based.*

5.1.1 Sampling Design

Our research relies on surveys of university-based NTBFs in the Netherlands and Germany. The samples are collected from (a) UBIs, (b) Academic Accelerators, and (c) University Innovation Centers. Here, we faced a specific challenge with university-based NTBFs in designing the sample. Our challenge is twofold: (1) a majority of universities has no complete database of their NTBFs, and (2) some of them resisted to provide us with the content of their database and referred us to contact their tenants directly via internet. So, we were unable to provide an equal chance to each individual in our potential population to participate in any survey. In other words, we could not approach a probability sampling strategy for our data collection (cf. Sarstedt and Mooi, 2019). As a result, we applied a non-probability sampling strategy and selected a purposive sample technique. According to this technique, the sample is selected based on the particular characteristics of a population. In Subsection 5.1.3 the idea is elaborated upon.

Following the determination of the population's characteristics, we have employed *four* different data resources to collect our sample of NTBFs. Below, we mention the resources that the researcher has used to build up her collection of entrepreneurs and co-founders who agreed to participate in the survey.

Resource 1: Due to the author's participation in the Yes!Delft incubation program (the author as a co-founder of an NTBF), she was able to access the initial list of the existing entrepreneurs and (co-)founders. Subsequently, she looked for their names on LinkedIn to make a connection with them and invited them to participate in the survey.

Resource 2: The author collected a list of all university-supported business incubators, accelerators and innovation centers in the Netherlands. Then, she contacted the program directors and asked them to send the survey link to their entrepreneurs via their network and invite them to fill in the survey. In the case that there was no support from the incubator / accelerator, the author searched for the list of the current NTBFs on their own website and invited the (co-)founders (220) via their LinkedIn IDs or via their contact address mentioned on their website.

Resource 3: We have used a snowball sampling technique (definition 5.2). During the invitation of NTBF founders, we asked them to introduce us to the other entrepreneurs with the same characteristics.

Resource 4: The fourth source for the data collection was through the participation in Start-up Meetups. Four examples are: (a) Science Meets Business by Leiden University Bio-Science Park, (b) Start-ups Pitching Day in Yes!Delft Incubator, (c) New Business Summit 2019 by World Start-up Factory, and (d) Thursday Gathering Events by Venture Café Rotterdam and Cambridge Innovation Centre (CIC).

It is worth mentioning that the author participated in all these events regularly and invited the entrepreneurs to participate in the study. For instance, in Start-up meetups by Venture Café Rotterdam, the author had an info table to present her research and invited entrepreneurs to collaborate in her academic work.

Definition 5.2: ***Snowball Sampling Technique*** *is a type of non-probability sampling method, which enables the researcher to make contact with a small number of members of the target group and then make new connections with other persons who fit the sample via their network (see Bryman, 2012).*

5.1.2 Data Collection

Data is collected via an online survey using web-based software **Qualtrics** (http://www.qualtrics.com), and **Google Forms** (https://docs.google.com/). Qualtrics is a leading web service provider that allows a specific type of respondent and the desired sample size to be chosen. The process of data collection started in September 2018 and ended in July 2019. We used the online format of the survey with an email invitation (see Appendix B). Within the process of data collection, 308 participants were invited. Of them, 220 participants were invited via LinkedIn and 68 of them were invited through sending the link of the survey directly to their email addresses. In addition to using the online application, I used the printed format of the survey. I disseminated 20 printed formats among the entrepreneurs in the Yes!Delft Venture Capitalists (VCs) Meetups.

In total, 308 (co-)founders were invited. Out of them, 111 responses were received. Finally, 96 responses were fully completed. Table 5-1 provides an overview of the list of incubators, accelerators and innovation centers that participated in the survey. It should be mentioned that the majority of the entrepreneurs requested not to mention the name of their NTBFs in the study. Therefore, we would not provide the names of the NTBFs that participated in our survey and restrict the report by only announcing the number of the NTBFs that participated in the survey from each business incubator or accelerator.

Table 5-1: List of the Accelerators/ Incubators/ Innovation Centers

Name of the Incubator/ accelerator/ innovation center	Number of Participants	Country
Yes!Delft (Delft University of Technology Business Incubator)	35	The Netherlands
Science Park of Delft University of Technology	3	The Netherlands
PLNT (Leiden University Business Incubator)	4	The Netherlands
Leiden University Bio-Science Park	3	The Netherlands
UtrechtInc (Utrecht University Business Incubator)	2	The Netherlands
ACE (UvA Business Incubator)	1	The Netherlands
ESA BIC Noordwijk	1	The Netherlands
Start up in residence Amsterdam	1	The Netherlands
World Startup Factory (Den Haag Accelerator)	2	The Netherlands
Crosspring	2	The Netherlands
ImpactPlus	1	The Netherlands
Rotterdam Cambridge Innovation Centre (CIC) and Venture Lab	7	The Netherlands
Wageningen University Business Incubator	1	The Netherlands
EIT Health Accelerator	33	Germany
Strascheg Center for Entrepeneurship (SCE)	1	Germany

Remark on the Sample Size

As a researcher and data analyst who mainly works with big data, I have to admit that in the era of big data our readers may have expected other numbers, based on the exponential growth in the number of studies with a massive amount of data in different fields of studies. Hence, it is evident that a sample size of 96 founders is a small number compared to the terabytes of any data sample. However, within this research, access to a large quantity of NTBFs was not possible to me. Compared to five similar relevant studies (see van Geenhuizen and Soetanto, 2009; Soetanto and Jack, 2016; Albort-Morant and Oghazi, 2016; Soetanto and Jack, 2018; Soetanto and van Geenhuizen, 2019), a sample size of 96 is adequate in the UBI and NTBFs domains. To inform the reader, the sample sizes of other recent studies in this domain are as follows.

Soetanto and van Geenhuizen (2019) with a sample size of n = 100, Soetanto and Jack (2016; 2018) with a sample size of n =141, Soetanto and van Geenhuizen (2009) with a sample size of n= 78, and Albort-Morant and Oghazi (2016) with a sample size of n = 54. So, it appears that conducted studies with a large sample size within the domain of our research are still not available.

5.1.3 Identification of the Target Population

Our goal is to arrive at a carefully selected target population. Therefore, we considered the following four criteria in our sampling selection process.

Criterion 1: The respondents should be the (co-)founders of the NTBFs. Therefore, at first, we identified only the entrepreneurs and then directly invited them to participate in the survey. Obviously, no people with other roles within NTBFs have been contacted to collaborate in our research. As we communicated only with (co-)founders, no section has been considered in the survey to identify the position of the participants in their NTBFs.

Criterion 2: The NTBFs should receive support from the public and university-supported incubators or accelerators.

Criterion 3: Students, graduates or academic staff have a role in the team of the NTBFs.

Criterion 4: The NTBFs need to meet the condition of technology-based firms. It means that they develop or commercialize new technologies, technology-based services or products (cf. Soetanto and Jack, 2016).

Pretesting the Survey

In order to make sure that the survey is comprehensible for the participants and to validate the measurement tool, we did two actions: (1) we revised the text and made some modifications in selecting the words to be more understandable for the target population, and (2) we assessed the content validity through the conduction of interviews with four entrepreneurs, three UBI managers and eight scholars. For these interviewees, we used the ***convenience sampling technique*** (see Bryman, 2012).

> **Definition 5.3**: ***The convenience sampling technique*** *is one type of the non-probability sampling techniques, which refers to a straightforwardly available sample (see Bryman, 2012).*

Concerning the convenient access to the academic scholars and entrepreneurs from the Netherlands, France, and Denmark, we were able to pretest the questionnaire in a satisfactory way with them. The scholars were the faculty members in Leiden University, Delft University of Technology, Aarhus Business School, and Université de Lorraine. The entrepreneurs worked in the Science Park of Delft University of Technology (e.g., InexTeam), and Leiden University Bio-Science Park (e.g., FilterLess). The managers (manager, program director, and director) worked in the Centre for Innovation of Leiden University and in the Leiden Bio-Science Park in the Netherlands. Table 5-2 provides an overview of the interviews to evaluate the measurement scales from NTBFs, and UBIs.

Table 5-2: List of Experts to Validate the Survey

Name of Organization	Evaluation study	Industry
FilterLess (NTBF)	Co-Founder	Computer and software industry (e.g., AI, Blockchain)
	Co-Founder	Computer and software industry (e.g., AI, Blockchain)
	Co-Founder	Computer and software industry (e.g., AI, Blockchain)
InexTeam (NTBF)	Co-Founder	Healthcare and Med-tech
Centre for Innovation (Leiden University)	Manager	University Business incubator
Centre for Innovation (Leiden University)	Program Director	University Business incubator
Leiden Bio-Science Park	Director	University Business incubator

5.2 Method of Analysis

In this section, we describe the statistical method of data analysis.

The statistical analysis technique widely used by researchers in the field of technology and innovation studies, is multivariate analysis. It consists of different statistical methods to simultaneously analyze multiple variables. The main types of statistical methods in multivariate analysis are divided into two categories: (1) primarily exploratory, and (2) primarily confirmatory. Within the exploratory methods the investigations used (a) search for new patterns and (b) facts that have not been explored so far. Here, we mention four of them: Cluster Analysis, Exploratory Factor Analysis, Multidimensional Scaling, and Partial Least Squares. They are the sorts of techniques of the primarily exploratory category. The confirmatory type of methods is applied when the researchers would like to test their hypotheses and explore the relationships between the variables. The category of the confirmatory type involves Analysis of Variance, Logistic Regression, Multiple Regression, Confirmatory Factor Analysis, and Covariance-Based Structural

Equation Modeling. These techniques are regression-based approaches. It is worthwhile to consider that the distinction between exploratory and confirmatory is not always clear and the techniques can be applied either to explore or confirm (see Hair et al., 2017).

Following the above discussion, it appears that the application of linear regression analysis as a confirmatory statistical method is an appropriate tool to test our theoretical model, the construct, and subsequently its hypotheses.

In the next section, the reports on the construct validity are presented.

5.3 Construct Validity

This section evaluates the validity of our construct. The evaluation process is based on the analysis procedure by Sarstedt and Mooi (2019). Their analysis procedure to evaluate the *construct validity* requires four steps: **(1) Evaluating the appropriateness of the data, (2) Extract the factors / components, (3) Determine the number of factors / components, and (4) Interpret the factor solution (Component Rotation).** The four steps are reported in the subsections 5.3.1 to 5.3.4. Table 5-3 demonstrates the distribution of questions (second column; questionnaire items) gives a survey over the six measurement scales (first column). Appendix C gives a detailed description of the questionnaire and its items.

Table 5-3: List of the Six Types of Questions Related to the Construct

Measurement Scale	Questionnaire Items
1. Innovation Strategy	0-12
2. Knowledge development and dissemination	13-26
3. Finance mobilization	27-31
4. Absorptive capacity	32-37
5. Finance capability	38-45
6. Performance	46-50

5.3.1 Evaluating the Appropriateness of the Data

The **first step** is to check whether our data is appropriate to employ variable reduction techniques (e.g., Principal Component Analysis and Principal Factor Analysis).

> **Definition 5.4.:** ***Variable Reduction Techniques*** *are the analysis methods (e.g., Principal Component Analysis, Maximum Likelihood, Image Factoring) that aim at finding interrelationships between variables to reduce the number of unifying ones.*

The main goal of the variable reduction techniques is described as follows: "These techniques concentrate to extract a minimum number of factors that account for a maximum proportion of the variables' total variance" (Sarstedt and Mooi, 2019, p.266).

The basis of the reduction techniques is identifying the correlations between variables. Therefore, to apply reduction techniques, the variables need to be sufficiently correlated. In this regard, we apply three well-known techniques to examine the adequacy of our sample: (A) correlation matrix, (B) Kaiser–Meyer–Olkin (KMO) criterion, and (C) Bartlett's test of sphericity. We explain them below.

A: Correlation Matrix

> **Definition 5.5:** *A* ***Correlation Matrix*** *is a table which shows the correlation coefficients between variables. The correlation matrix analyses the strength of the relationship between variables on the scale from -1 to +1 (see Field, 2018).*

To test the *sufficiency* of the variable's correlations, the correlation matrix should show the correlation coefficients with a value above 0.3. The correlation matrices of the three independent variables (i.e., innovation strategy, knowledge development cs, and finance mobilization) and two moderators (i.e., absorptive capacity, and financial capability) are given in Table 5-4. Hence fort we will use knowledge development cs when we mean knowledge development and dissemination. The item operationalization of these expected variables is presented in Appendix D1 and D2. The D1 matrix associated with independent variables shows that 112 coefficients are above the 0.30 threshold criterion. It also depicts that 31 items of innovation strategy, knowledge development and dissemination (henceforth knowledge development cs), and finance mobilization are correlated. The D2 matrix associated with moderators reveals that 16 coefficients are above the 0.30 threshold criterion. Nine items of the absorptive capacity and financial capability are correlated as well.

The correlation matrix (Table 5-4) shows significant correlations between knowledge development cs and innovation strategy (r = .290), between knowledge development cs and finance mobilization (r = .457), and between finance mobilization and innovation strategy (r = .208). Therefore, we may conclude that some of the variables are correlated with each other. Thus, PCA can be an appropriated technique (see Field, 2018).

Table 5-4: Correlation Matrix of the Expected Variables

Independent Variables	**Innovation Strategy**	**Knowledge Development**	**Finance Mobilization**
Innovation Strategy	1.000		
Knowledge Development CS	**.290****	1.000	
Finance Mobilization	**.208***	**.457****	1.000
Moderator Variables	**Absorptive Capacity**	**Financial Capability**	
Absorptive Capacity	1.000		
Financial Capability	**.368****	1.000	

*. Correlation is significant at the 0.05 level (2-tailed)

B: The Kaiser–Meyer–Olkin (KMO) Criterion.

> **Definition 5.6**: ***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).*

The KMO criterion also demonstrates the correlations between variables and adequacy of the sample. A small value of this index would show low appropriateness of the construct (cf. Sarstedt and Mooi, 2019). According to this measure score, the KMO index should be above 0.50 to be suitable for the variable reduction techniques.

Table 5-5 reports the computed KMO index of the independent variables with a value of 0.714, and moderator variables with a value of 0.621, which both are above the threshold level of 0.50. As a result, the reported KMOs approve the adequacy of (1) the sample and (2) the sufficient correlation of the variables for the analysis.

Table 5-5: The Results of KMO Index

	Independent Variables	**Moderators**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.714	.621

C: Bartlett's Test of Sphericity

The Bartlett's Test of Sphericity index indicates whether the correlation matrix is proportional to an identity matrix (cf. Field, 2018). The Bartlett's test needs to be a very limited value ($p < 0.050$) to reveal that the variables are sufficiently correlated and are suitable for variable reduction techniques.

> **Definition 5.7:** ***Bartlett's Test of Sphericity*** *indicates whether the correlation matrix is an identity matrix, which would indicate that the variables are unrelated (cf. Sobh, 2008).*

The Table 5-6 indicates that Bartlett's test is significant at 0.000, which verifies that the variables are sufficiently correlated.

Table 5-6: The Results of Bartlett's Test

Independent Variables			Moderators		
Bartlett's Test of Sphericity	Approx. Chi-Square	1564.778	Bartlett's Test of Sphericity	Approx. Chi-Square	282,597
	df	496		df	91
	Sig.	.000		Sig.	.000

In conclusion, the results of the correlation matrix, KMO index, and Bartlett's test show that our data is adequate to conduct variable reduction techniques.

5.3.2 Extract the Factors / Components

The **second step** is to extract the factors / components. To conduct variable reduction techniques, it is necessary to determine which techniques are adequate for the data set (i.e., PCA or Factor Analysis). We briefly discuss the choice between (A) PCA and Factor Analysis and (B) Factor/ Component Extraction.

A: Principal Component Analysis (PCA) or Principal Factor Analysis

Principal Component Analysis (PCA) and Principal Factor Analysis (PFA) are two similar techniques to identify patterns and structures in a group of observed variables (cf. Sarstedt and Mooi, 2019). Although the two techniques are similar in a way that they reach a solution, they *differ in their goals* and in their approach to find a solution. The goal of the PCA is to reduce a number of variables (here called components) to a set of smaller observed variables. However, the goal of PFA is to identify the underling dimensions (here called factors) (cf. Sarstedt and Mooi, 2019).

PCA use the correlations between the variables, thus PCA should be applied when there exists a correlation between variables. The focus of the research is to extract a minimum number of components which represent a maximal set of total variances of the variables. In contrast, PFA should be used when the focus of research is to *identify* latent dimensions count for the variables (cf. Sarstedt and Mooi, 2019).

Hence, we prefer PCA. Thus, we check the possible correlation between the variables to choose an application of the PCA technique.

Table 5-4 presents the correlation matrix of the three variables: innovation strategy, knowledge development cs and finance mobilization. We see from the results that there are significant correlations between finance mobilization and knowledge development cs ($r = 0.457$), between knowledge development cs and innovation strategy ($r = 0.290$), and between finance mobilization and innovation strategy ($r = 0.208$). In addition, there is a significant correlation between two moderators (e.g., absorptive capacity and finance capability) ($r = 0.368$). Hence, we may conclude that there are correlations between some of the variables and we are allowed to continue the analysis with Principal Component Analysis.

> **Definition 5.8:** *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. PCA is a multivariate analysis technique for identifying the linear components of a set of variables (cf. Pallant, 2010; Field, 2018).*

B: Component Extraction

Reduction techniques aim to generate a new data structure with fewer factors (variables). In order to extract the components, PCA computes the eigenvectors. The eigenvectors extract the maximum possible variance of all the variables (cf. Sarstedt and Mooi, 2019). Eigenvalues of a covariance are the core of PCA.

> **Definition 5.9**: ***Eigenvalue** explains the total amount of variance by each variable (Sarstedt and Mooi, 2019), and quantifies to what extent the variances of the matrix are distributed (Field, 2018).*

5.3.3 Determine the Number of Factors / Components

The **third step** determines the number of components to be extracted. This step is a challenging one in PCA. Different approaches are conducted to identify the number of components to be extracted. In this respect, multiple approaches are recommended to be employed to provide greater confidence in the results. We will conduct the three approaches to determine the number of components to be extracted. (A) Kaiser's criterion; (B) The Scree Plot of Eigenvalues; (C) Parallel Analysis. They are described below.

A: Kaiser's Criterion

Definition 5.10: ***Kaiser's Criterion*** *is the rule to drop all components with eigenvalues under 1.0 (cf. Kaiser, 1960).*

According to this approach, the Eigenvalue with value greater than 1 determines the number of components to be extracted. Table 5-7 reveals the results of the PCA with the values of the Eigenvalues.

The results show that 9 variables (here called components) related to Independent Variables have obtained Eigenvalues greater than 1 which meet the Kaiser's criterion. These components demonstrate 24.858%, 10.362%, 9.165%, 6.746%, 5.660%, 4.180%, 3.788%, 3.637%, and 3.281% of variance (third column).

Moreover, the results show that 6 components related to the **Moderators** have obtained Eigenvalues greater than 1 which meet the Kaiser's criterion. These components demonstrate 23.458%, 12.027%, 10.374%, 8.789%, 8.502% and 7.267% of variance (third column).

Table 5-7: Eigenvalues Extracted through the PCA Component for independent Variables

Total Variance Explained- Independent Variables			
	Initial Eigenvalues		
Components	Total	% of Variance	Cumulative %
1	**7.955**	24.858	24.858
2	**3.316**	10.362	35.220
3	**2.933**	9.165	44.385
4	**2.159**	6.746	51.131
5	**1.811**	5.660	56.790
6	**1.338**	4.180	60.971
7	**1.212**	3.788	64.759
8	**1.164**	3.637	68.396
9	**1.050**	3.281	**71.677**
…			
31	.097	.303	99.803
32	.063	.197	100.000

Table 5-8: Eigenvalues Extracted through the PCA Component for Moderators

Total Variance Explained- Moderators			
	Initial Eigenvalues		
Components	Total	% of Variance	Cumulative %
1	**3.284**	23.458	23.458
2	**1.684**	12.027	35.484
3	**1.452**	10.374	45.858
4	**1.231**	8.789	54.648
5	**1.190**	8.502	63.150
6	**1.017**	7.267	**70.417**
…			
14	.301	2.152	100.000

Overall, the results show a cumulative variance of 71.677% for Independent Variables, and 70.417% for Moderators (fourth column of Table 5-7 and Table 5-8).

Based on the results in Table 5-7, 23 components in the independent variables (from 10 to 32), and in Table 5-8, 8 components in the moderators (7 to 14) have low Eigenvalues (see the full table in Appendix E1 and E2). Accordingly, they should be rejected.

However, the number of components to extract from Kaiser's criterion is not a perfect approach (see Sarstedt and Mooi, 2019). Therefore, Scree Plot and Parallel Analysis need to be considered and compared with the results of Kaiser's criterion.

B: Scree Plot

The second approach to identify the number of components to extract is Scree Plot. The scree plot indicates the *relative importance* of each component (cf. Field, 2018).

> **Definition 5.11**: ***Scree Plot*** *is a graph in which each eigenvalue (Y-axis) in plotting against the components with which it is associated (X-axis) (cf. Field, 2018).*

The Scree Plots for (a) the Independent Variables (see Figure 5-1) and (b) the Moderators (see Figure 5-2) are depicted. The relative importance is defined by component matrix (eigenvalues) when the differences in eigenvalues are negligible

Figure 5-1: Scree Plots Associated with Independent Variables

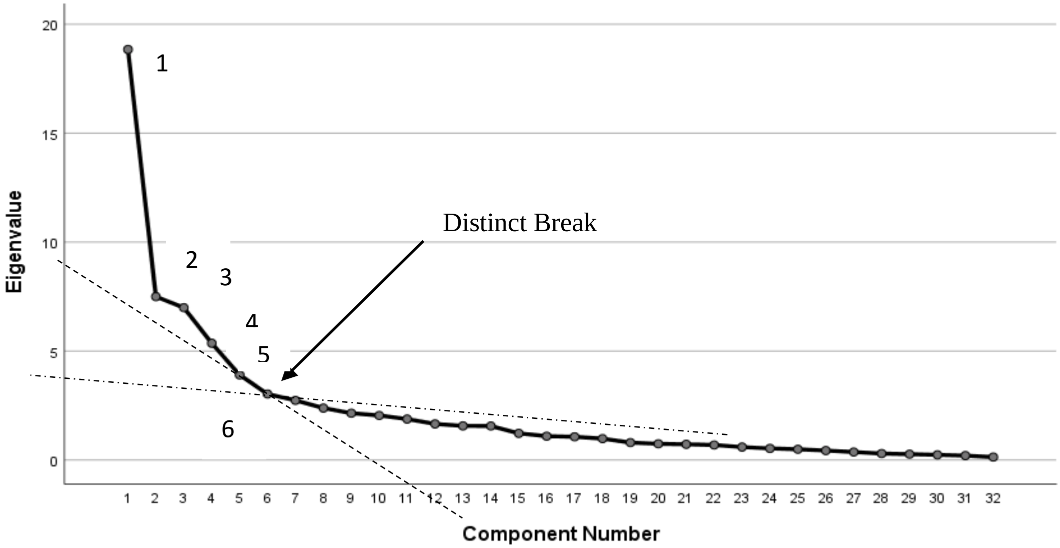
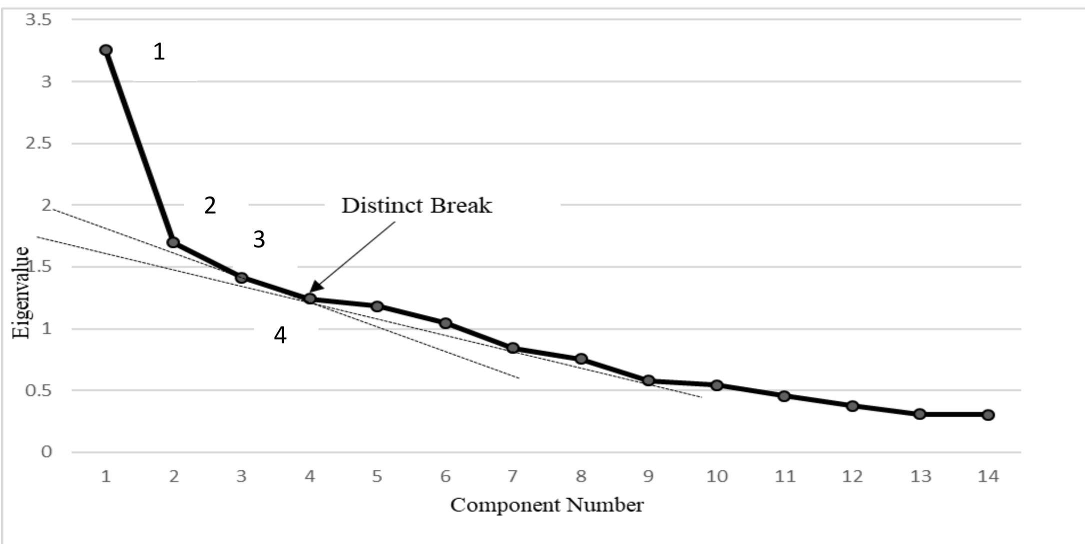


Figure 5-2: Scree Plots Associated with Moderators



The first Scree Plot computed is associated with the Independent Variables and highlights the distinct break (or elbow). We see that which the retaining components are above this break. The plot demonstrates that components 1, 2, 3, 4, 5 and 6 are above the elbow. Thus, from this plot we can decide six components to extract.

The distinct break in the second Scree Plot associated with moderators reveals that the components 1, 2, 3 and 4 are above the elbow. Therefore, based on this distinct break, four components can be extracted.

However, as the results of the plot are not statistically decided upon, the judgment of the number of components to extract is not accurate. Therefore, we include a third analysis method, the Parallel Analysis.

C: Parallel Analysis

> **Definition 5.12:** ***Parallel Analysis*** *is a Monte-Carlo-Simulation-based method that allows determining the number of components to retain in the Principal Component Analysis (cf. Ledesma and Valero-Mora, 2007).*

The method compares the observed Eigenvalues (raw data) extracted from the correlation matrix to be analysed with those obtained from uncorrelated normal variables (cf. Ledesma and Valero-Mora, 2007).

Among the mentioned approaches (e.g., Kaiser's criterion, Scree Plot, and Parallel Analysis) for identifying the number of components to extract, Parallel Analysis is the most accurate and reliable approach (see Sarstedt and Mooi, 2019; Field, 2018).

To extract the number of components with Parallel Analysis, we run the Syntax developed by O'Connor (2000) in SPSS (see Appendix F). The results of the analysis are reported in Table 5-9. In the table, the third column labeled Prcntyle reveals the 95th percentile for each factor's eigenvalue. This column needs to be compared with the second column (initial eigenvalues). Previously, the Subsection 5.3.3(A) demonstrated the initial eigenvalues (see Table 5-7 and Table 5-8). The number of components to extract will be identified through the comparison between initial eigenvalues and Prcntyle.

The Final Outcome of Step 3

Table 5-9 shows that four components associated with independent variables have greater initial eigenvalues than their Prcntyle. Two components associated with moderators have greater initial eigenvalues than their Precntyle. Therefore, the results of Parallel Analysis demonstrate that the number of components to extract for further analysis related to the individual variables is ***four*** and the number related to the moderators is ***two***.

These four components have the variance of 24.858%, 10.362%, 9.165%, and 6.746% (see Table 5-7). Overall, the cumulative variance of these four components is 51.131% (see Table 5-7).

The two components associated with moderators have the variance of 23.458%, and 12.027% (see Table 5-8). The cumulative variance of these three components is 35.484 % (see Table 5-8).

Table 5-9: The Result of Parallel Analysis

Component *(Independent variables)*	**Initial Eigenvalues**	**Prcntyle**	**Decision**
1	**7.954521**	**2.532995**	**Accept**
2	**3.315843**	**2.282646**	**Accept**
3	**2.932795**	**2.094688**	**Accept**
4	**2.158695**	**1.958615**	**Accept**
5	1.811097	1.841834	**Reject**
6	1.337753	1.720791	**Reject**
7	1.212212	1.616428	**Reject**
…	…	…	**Reject**
32	.062912	.228015	**Reject**

Component *(Moderators)*	**Initial Eigenvalues**	**Prcntyle**	**Decision**
1	**3.284**	**1.878902**	**Accept**
2	**1.684**	**1.664605**	**Accept**
3	1.452	1.408921	**Reject**
4	1.231	1.355423	**Reject**
…	…	…	**Reject**
14	.301	.505338	**Reject**

5.3.4 Interpret the Factor Solution (Component Rotation)

In the **fourth step**, we interpret the factor solution following the procedure by Sarstedt and Mooi (2019). The procedure is as follows. (1) the component rotation is conducted. Then, (2) we determine the variables that are relevant to the extracted factors as computed in the previous step. Finally, (3) we compute the components scores.

> **Definition 5.13**: ***Component Rotation*** *determines what the components represent. It shows the estimation of correlations between the variables and the estimated components (Field, 2018).*

The component rotation has two types of methods: (1) Orthogonal, and (2) Oblique rotation method. To perform the component rotation, we need to conduct it with one of the mentioned methods. In this regard, the correlations between our variables should be conducted to indicate which method is adequate to perform. Within Orthogonal methods (e.g., Varimax, Quartimax, and Equamax) the variables are not correlated. In contrast, Oblique rotation methods (Oblimin, and Promax) presume that there are correlations between variables ($r > 0.3$). Therefore, we test our data in SPSS to explore which rotation method is adequate to our construct.

> **Definition 5.14**: *An* ***Oblique Rotation*** *is a method of rotation in factor analysis that allows the underlying factors to be correlated (Field, 2018).*

Rotation is a process in factor analysis for improving the interpretability of factors. In essence, an attempt is made to transform the factors that emerge from the analysis in such a way as to maximize factor loadings that are already large and minimize factor loadings that are already small (Field, 2018).

The results of our analysis are presented in Table 5-10. In this table, the correlations between the components are reported. It shows that the highest value of the correlation is 0.350, which meets the threshold criterion ($r > 0.3$).

Table 5-10: Component Correlation Matrix Associated with All Variables

Component Independent variables	1	2	3	4
1	1.			
2	-.152	1.		
3	.114	-.004	1.	
4	**.350**	-.096	.091	1.

Component Moderators	1	2
1	1.	0.271
2	0.271	1.

According to the outcome of the Table 5-10, for Independent Variables, we can continue our analysis with the Promax rotation technique under the Oblique rotation methods category. For Moderators, the component correlation is 0.27 which is under threshold criterion. Therefore, we continue the analysis of the Moderators with Varimax rotation technique under the Orthogonal methods category.

Definition 5.15: *"**Promax Rotation** a method of oblique rotation that is computationally faster than direct oblimin and so useful for large data sets" (Field, 2018, p.1300).*

Definition 5.16: ***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).*

The results of conducting Promax rotation technique on the Independent Variables and Varimax rotation technique on the Moderators are presented below in subsections ***A*** and ***B***.

***A**: Promax Rotation Method on the Independent Variables*

The outcome out of performing the Promax rotation method on the independent variables is depicted in Table 5-11. This table evaluates the construct validity. The criteria for the acceptable construct validity are:

(1) component-loadings should be higher than 0.6, and

(2) the cross-loadings need to be below 0.3.

The results of the initial component rotation reveal that eight items associated with component 1; six items associated with component 2; five items associated with component 3; and four items associated with component 4 have component-loadings higher than 0.6, and cross-loadings below 0.3. Therefore, we continue the analysis with the four components and the highlighted items. The rest of the items below 0.6 will be excluded.

Table 5-11: First Pattern Matrix on Independent Variables

	Component			
ITEM	1	2	3	4
Q17	**.861**			
Q15	**.848**			
Q19	**.834**			
Q18	**.809**			
Q14	**.762**			
Q16	**.751**			
Q20	**.729**			
Q13	**.727**			
Q6	.378		.363	
Q5	.306			
Q4				
Q21		**.830**		
Q22		**.794**		
Q23		**.780**		
Q24		**.774**		
Q25		**.746**		
Q26		**.701**		
Q29			**.785**	
Q31			**.748**	
Q27			**.716**	
Q28			**.707**	
Q30			**.692**	
Q1				
Q2				**.661**
Q8				**.643**
Q7				**.626**
Q11				**.615**
Q9				.584
Q12				.545
Q0				.541
Q3				.519
Q10		-.335		.478

Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.

After excluding the items below 0.6 component-loadings, the next rotation component matrix is run and presented in Table 5-12. To perform the final rotation, we exclude nine out of thirteen items from innovation strategy variable. This exclusion improves the construct validity. The rest of the items associated with knowledge development and dissemination and financial mobilization retain.

Table 5-12: Final Parallel Matrix Rotation Solution on Independent Variables

	Component			
Item	1	2	3	4
Q17	**.877**			
Q19	**.847**			
Q15	**.844**			
Q18	**.823**			
Q16	**.766**			
Q14	**.750**			
Q20	**.731**			
Q13	**.723**			
Q21		**.840**		
Q22		**.815**		
Q23		**.806**		
Q24		**.795**		
Q25		**.746**		
Q26		**.736**		
Q29			**.820**	
Q28			**.767**	
Q31			**.735**	
Q30			**.724**	
Q27			**.684**	
Q8				**.766**
Q2				**.712**
Q7				**.682**
Q9				**.615**
Q11				**.600**

Extraction Method: Principal Component Analysis.

In the final rotation matrix to ensure acceptable construct validity, the items with component-loadings below 0.6 and cross-loadings above 0.3 should be excluded. Consequently, no items of the four components were excluded. The final rotation (see Table 5-12) shows that five items (Q2, Q7, Q8, Q9, Q11) out of thirteen associated with innovation strategy; fourteen items (Q13-Q26) associated with knowledge development and dissemination; and five items (Q27-Q31) associated with financial mobilization. Thus, the original thirteen items referring to the innovation strategy is reduced to the five items, and the original fourteen items associated with knowledge development and dissemination and five items associated with financial capability are remained. With the validated construct related to the independent variables, we are able to evaluate the construct reliability. Therefore, Cronbach's Alpha and Composite Reliability will be calculated for the three remaining variables (i.e., the validated four components).

***B**: Varimax Rotation Method on the Moderators*

The results out of conducting the Varimax rotation method on the moderators is presented in Table 5-13. According to the criteria for the acceptable construct validity (having the items with component-loadings above 0.6 and cross-loadings below 0.3), Table 5-13 shows that three items associated with component 1 and one item associated with component 2 have component-loadings higher than 0.6, and cross-loadings below 0.3. Thus, these four items (see Table 5-13) will remain for further analysis. To ensure acceptable construct validity, we decide to exclude three items out of the original six items related to the absorptive capacity, and seven items out of the original eight items related to the financial capability to increase the construct validity. Consequently, we continue the analysis with two components and four bolded items.

Table 5-13: First Rotation on the Moderators

	Component	
	1	2
Q32	**.618**	.126
Q33	**.615**	-.360
Q41	.152	**.696**
Q36	**.661**	-.155
Q34	.523	.098
Q35	.339	-.108
Q37	.377	-.397
Q38	.445	-.296
Q39	.484	-.337
Q40	.228	.414
Q42	.474	.396
Q43	.548	.053
Q44	.494	.574
Q45	.503	-.047

Extraction Method: Principal Component Analysis.

Following excluding the items with below 0.6 component-loadings, the outcome of next rotation component on the Moderators is depicted in Table 5-14.

Table 5-14: Final Rotation Matrix on Moderators

	Component	
	1	2
Q32	**.756**	.391
Q33	**.778**	-.282
Q41	.074	**.938**
Q36	**.758**	-.192

Extraction Method: Principal Component Analysis.

This final rotation on moderators demonstrates that all the remained items have component-loadings above 0.6 and cross-loadings below 0.3. The three remaining items (Q32, Q33, and Q36) in component 1 are associated with absorptive capacity and one item (Q41) loaded in component 2 is associated with financial capability. Therefore, the original six-item scale related to the absorptive capacity is reduced to a three-item scale and the original seven-item scale referring to the financial capability is reduced to a one-item scale. However, a minimum of three items for each variable (i.e. component) with component-loadings above 0.6 is required to perform further analysis (cf. Field 2018). As a consequence, financial capability is not currently supported by sufficient items and should be rejected. In other words, component 2 which is mainly loaded through an item associated with the financial capability scale (see Table 5-14), it is decided to be excluded to improve the construct validity. We continue the analysis with one Moderator (i.e., absorptive capacity).

Having the validated construct related to the moderators, we are able to evaluate the construct reliability for the moderators. Subsection 5.4 reports the results of the reliability analysis.

5.4 Construct Reliability

For measuring the internal consistency (i.e., reliability) of the variables in the construct, **Cronbach's Alpha (**subsection 5.4.1) and **Composite Reliability** (subsection 5.4.2) criteria are suggested to be computed (see Joseph et al., 2017).

5.4.1 Cronbach's Alpha

> **Definition 5.17**: ***Cronbach's Alpha*** *is a commonly used test of internal reliability. It calculates the average of all possible split-half reliability coefficients.*

Cronbach's Alpha has a positive relationship with the intercorrelations among the test items. The intercorrelations among the test items will be maximized when all items measure the same construct. Cronbach's Alpha is accepted as an indicator of the entity's reliability (cf. Cronbach, 1951; Gliem and Gliem, 2003).

A computed Cronbach's Alpha will vary from 0.0 (no internal reliability) to 1.0 (perfect internal reliability). The acceptable range of Cronbach's Alpha is as follows:

- below 0.5 unacceptable
- above 0.5 undesirable
- above 0.6 questionable
- above 0.7 acceptable
- above 0.8 good
- much above 0.9 excellent (Gliem and Gliem, 2003).

The results of our reliability analysis are presented in Table 5-15. According to the mentioned range, the calculated results show that finance mobilization with 0.829, innovation strategy with 0.704, and absorptive capacity with 0.752 Cronbach's Alpha coefficients have a respectable internal consistency. The knowledge development and dissemination with 0.903 Cronbach's Alpha coefficients has an excellent internal consistency.

However, Cronbach's Alpha generally tends to underestimate the internal consistency reliability. Therefore, to overcome the limitation of Cronbach's Alpha, Composite Reliability as a measure of internal consistency is recommended (see Joseph et al., 2017).

5.4.2 Composite Reliability

> **Definition 5.18**: "***Composite Reliability*** *is the total amount of true score variance in relation to the total scale score variance" (Brunner and Süß, 2005, p.229).*

Composite Reliability's values vary between 0 and 1, and it has the same interpretation as Cronbach's Alpha (values of 0.60 to 0.70 are acceptable; values between 0.70 and 0.90 are satisfactory). Thus, the higher value reveals higher internal consistency (see Joseph et al., 2017).

In contrast to the Cronbach's reliability, composite reliability overestimates the results of internal consistency. Thus, it has been suggested to consider both criteria (see Joseph et al., 2017). Accordingly, the third column of Table 5-15 shows the results of composite reliability. It is obvious that all the variables are above 0.70. Hence, the construct has a satisfying internal consistency.

Table 5-15: Construct Reliability

Variables	**Cronbach's Alpha**	**Composite Reliability**
Finance Mobilization	0.829	0.877
Innovation Strategy	0.704	0.735
Knowledge Development and Dissemination	0.903	0.915
Absorptive Capacity	0.752	0.771

The above steps complete the evaluation of the validity and reliability of the construct. The following section summarizes the results of the evaluated validity and reliability.

5.5 Results of the Construct Validity and Reliability

The results of the sample analysis reveal a good validity and a good reliability. The final rotated matrix related to the independent variables (Table 5-12) shows that the items (Q2, Q7, Q8, Q9, and Q11) associated with innovation strategy; the items (Q13-Q26) associated with knowledge development and dissemination; and the items (Q27-Q31) associated with finance mobilization have component-loadings above 0.6 and cross-loadings below 0.3.

Similar to the independent variables, the final rotated matrix related to the moderators (Table 5-14) demonstrates that the items (Q32, Q33, and Q36) associated with absorptive capacity have component-loadings above 0.6 and cross-loadings below 0.3. Good construct validity is achieved when these two threshold criteria are met. These results approve that our construct has a good validity.

In terms of the construct reliability, two criteria have been evaluated (1) ***Cronbach's Alpha,*** and (2) ***Composite Reliability.*** The results of reliability analysis show that both Cronbach's Alpha and Composite Reliability for the main variables (innovation strategy, knowledge development and dissemination, finance mobilization, and absorptive capacity) are above the threshold criteria (0.70). Good construct reliability is evident as Cronbach's Alpha coefficients and Composite Reliability are both above 0.70. Therefore, the construct addresses a good validity as well. Method validity will be addressed in subsection 6.4.2.

5.6 Answer to RQ2

This chapter addressed RQ2: *How can the supportive activities be operationalized in a construct that enables us to measure the impact of the identified supportive activities by UBIs on the performance of an NTBF?*

To provide an answer to this question and validate the measurement instrument (i.e., construct), we evaluated in this chapter the construct validity and reliability. The results of the evaluation of the construct validity show that eight items of the innovation strategy, seven items of the financial capability, and three items of the absorptive capacity should be excluded to improve the construct validity. Within the other variables (knowledge development and dissemination, and finance mobilization) their original fourteen and five items retained. Subsequently, the results of the analysis on the construct reliability demonstrate the acceptable and good reliability of our construct. In the next chapter, we will test our hypotheses with the new and adapted construct.

The provided answers given in chapter 4 (steps 1-3) and in chapter 5 (step 4) together form a solid answer to the RQ2.

In summary, the answers to RQ2 are as follows.

- A theoretical model is developed that associates the two supportive activities by UBIs, their related moderators and the NTBF’s innovation strategies with the performance of the NTBTs (Chapter 4).
- A measurement tool (construct) is provided to enable us to measure the possible impact of the support by UBIs on the performance of the NTBFs (Chapter 4).
- Validity construct analysis excludes the problematic scales of the construct to produce good construct validity (Chapter 5).
- Reliability construct analysis shows acceptable and good construct reliability for the retained construct (Chapter 5).