1ZM31 Multivariate Data Analysis(2017/2018)

Group Assignment 1

Report

Multivariate Data Analysis

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Data Exploration and Exploratory Factor Analysis

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Explore the Data

1. Compare the proportion of enterprises that launch innovations that are new to the market across the four sectors.

As shown in the next table, the sector of “knowledge-intensive-industries” has the greatest proportion of enterprises new to the market (54.5%), while “others-services” sector has the lowest (18.5%).

	Services	Industry
Others	18.46%	24.22%
Knowledge-Intensive	34.21%	54.50%

Table 1. Proportion of enterprises new to market according to sector

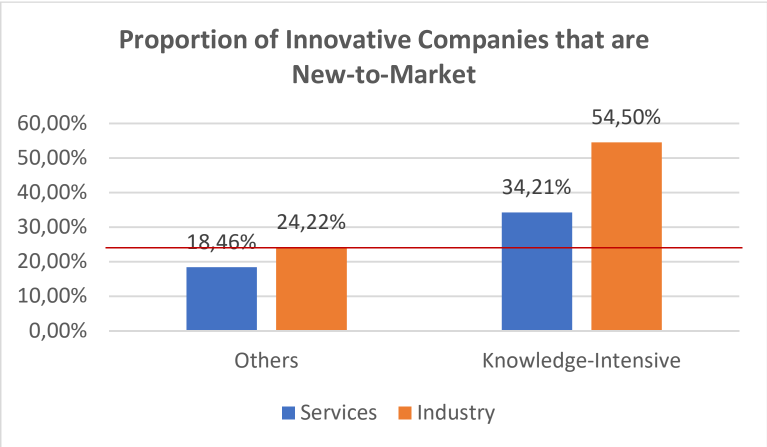


Figure 1. Comparison across 4 sectors for new to market enterprises

The “knowledge-intensive” sectors have the greatest proportion of new to the market enterprises in comparison to “others” and apparently “Industry” sector has the greatest proportion of new to the market enterprises in comparison to “Services” sector but this will be proved in the next question.

2. Are new to the market innovations more common in industry than in services? In your answer, report the exact percentages

Yes, new-to—market (NTM) innovations are more common in industry than in services since its proportion of NTM is 35.21% while services proportion is 27.81%.

3. For each of the 15 variables in the data file, indicate of what type they are and explain why. Choose from nominal scale, ordinal scale, interval scale or ratio scale.

The types of variables for the 15 variables of this case (with its argumentation) are:

- Sector: Nominal scale – It has nonmetric data and is a categorical variable (no ordering)
- Empuni: Ordinal scale – although it wants to represent percentage (metric data), this variable is nonmetric since it represents a range of percentages and has an ascendant order.
- InnovTurnoverP: Ordinal scale – it is a nonmetric variable representing a range of percentages with an ascendant order.
- Margin: Ordinal scale – the coding makes the variable nonmetric but there is ordering according to the percentages of margin.
- New-To-Market: Nominal scale – It has nonmetric data with dummy variable that represents "No" with a 0 and "Yes" with a 1.
- Competences (This groups the 10 competences): Ordinal scale – all of competences are ordinal since the answers had a coding of 1 (not existing) to 5 (strongly distinct) but there is ordering pattern.

4. Do firms that launch innovations that are new to the market rate themselves higher in terms of their margin?

No, there is no statistical difference between New-To-Market and No-New-To-Market enterprises since the confidence interval (CI at 95%) of t-test includes the value 0.

Paired T-Test: $CI_{95\%} = [-0.22\ , 0.42]$

Visually, the following boxplot supports what was stated before.

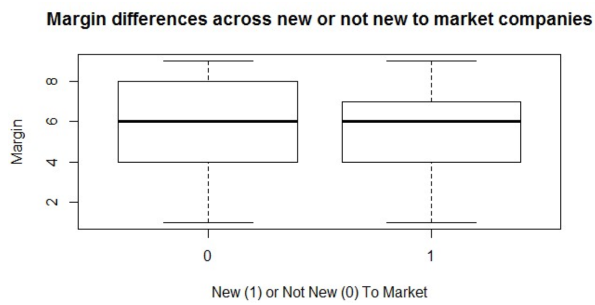


Figure 2. Boxplot for differences of margin in companies new and not new to market

Missingness in the Data

5. Do any of the variables contain missing values? If so, which variable(s)?

Yes, only the variable “EmpUni” – that represents ranges of percentage of employees holding a university degree – has missing values; in fact, there are 34 missing values.

6. What is the percentage of missingness?

The percentage of cases for which there is missing data is 3.90%

7. Are any of the competence variables related to the missingness? If so, which competence variable(s) are related to the missingness? Describe the procedure you have followed and report the results.

Yes, there are competence variables related to missingness; in fact, 4 out of the 10 competences are related to the missingness:

- Competence 3 – Scope for development via ‘trial and error’
- Competence 4 – Strong individual responsibility of employees
- Competence 6 – Incentive schemes for employees to innovate
- Competence 7 – Internal co-operation between departments / firm units

To come to this conclusion the procedure followed was:

Figure 3. Process to find relation between competence variables and missing values

The t-tests showed that there was significant difference between means of completed cases and missing value cases for competence 3,4,6 and 7 since the Confidence Interval (CI 95%) didn’t include value 0:

		Unpaired t-tests for means of complete cases vs missing values cases									
		Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	Comp. 6	Comp. 7	Comp. 8	Comp. 9	Comp. 10
CI (95%)	Lower	-0.20	-0.09	0.07	0.09	-0.04	0.17	0.12	-0.01	-0.10	-0.14
	Upper	0.58	0.76	0.83	0.81	0.69	0.90	1.08	0.84	0.67	0.60

Table 2. Unpaired T-Tests for competences variables comparing complete cases with missing values cases

8. Based on your answer to the previous question, is the missingness completely at random? Explain why or why not.

No, it is not completely at random (MCAR). Because competence 3, 4, 6 and 7 showed a difference in the unpaired tests as shown in Table 2, it should be considered as missing at random (MAR).

9. Can the missingness be ignored by dropping the enterprises with missing values? Why or why not?

No, missingness in this case cannot be ignored by dropping the enterprises with missing values because missingness is not catalogued as MCAR. Since the missingness is considered MAR, the missingness should be modeled instead of ignored.

Outliers

10. Compute the Mahalanobis distance of the enterprises based on the competence variables. Graphically present the Mahalanobis distances.

First, the means and covariations of competence variables were calculated to obtain mahalanobis distances. The mahalanobis distance of the enterprises were calculated on R and the resultant plot was:

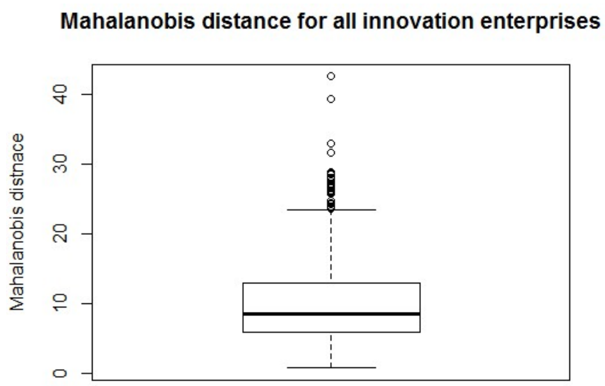
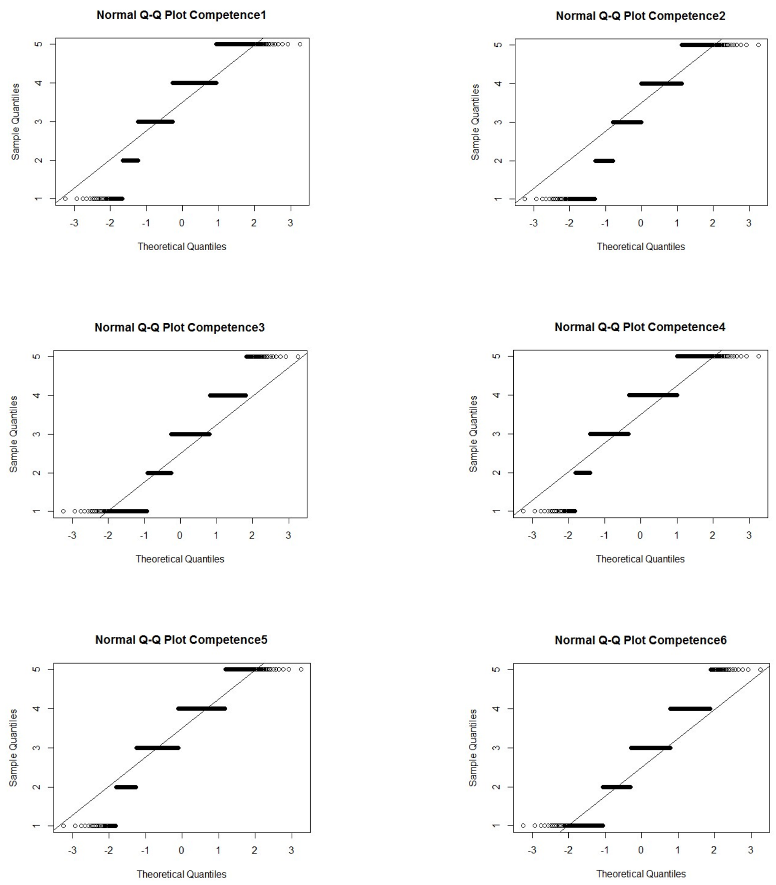


Figure 4. Mahalanobis distance for enterprises based on competence variables

11. Can we use the rule-of-thumb that observations of which the Mahalanobis Distance divided q is larger than 3 are outliers?

No, the rule-of-thumb cannot be applied in this case because the data for each competence variables is not normally distributed. To prove that the data was not normally distributed the qqplot's of the 10 competences were graphed (Figure 5) and also a Shapiro-test was run[1].



[1] According to Missouri-Kansas university in the page http://p.web.umkc.edu/pruer/which_test/shapiro.wilks.html a Shapiro Test can be done to categorical data that has more than 30 observations.

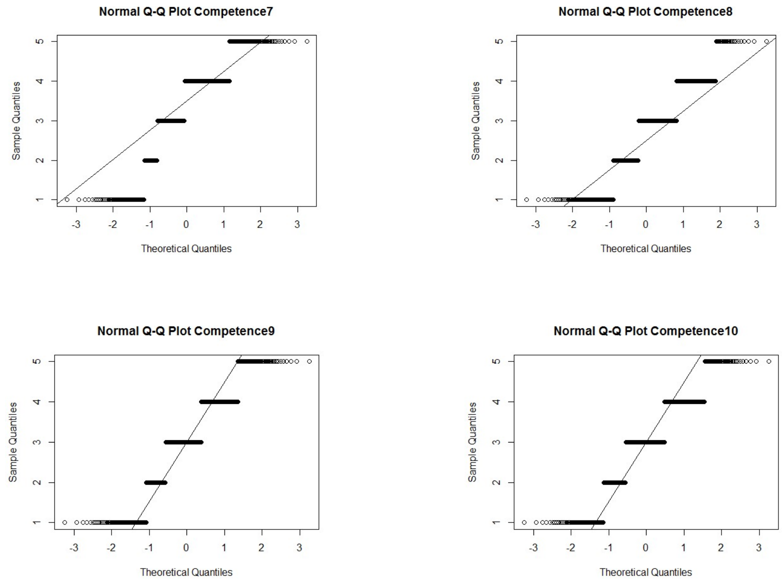


Figure 5. Q-Q Plots for testing normality in the ten competence variables

The Q-Q plots show that the data deviates from the normal Q line at the tails mostly, leading to a non-normal distribution. In other hand, for a no-visual test but a statistical one, a Shapiro test was run[2].

$$H_0: Data\ is\ normally\ distributed$$

$$H_1: Data\ is\ NOT\ normally\ distributed$$

		Shapiro Wilks test for normality									
		Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	Comp. 6	Comp. 7	Comp. 8	Comp. 9	Comp. 10
Shapiro	P-Value	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16
	W	0.87	0.89	0.90	0.85	0.87	0.90	0.87	0.90	0.90	0.90

Table 3. Shapiro Wilks Test for normality results for 10 competence variables

According to Table 3, all the P-Values were less than 0.05 which leads to reject H_0, showing that data is not normally distributed.

12. Which enterprises, if any, are outliers? Describe the decision process by which you have identified outliers.

There are not outliers considered in this case because the biggest MD/q quotient in the data is 4.25; that is not an extremely large quotient compared to 3 that is the rule-of-thumb, so the judgment is to keep it.

[2] According to Missouri-Kansas university in the page http://p.web.umkc.edu/pruer/which_test/shapiro.wilks.html a Shapiro Test can be done to categorical data that has more than 30 observations.

Exploratory Factor Analysis

13. Is a factor analysis appropriate for the competence questions? Explain how you have checked whether factor analysis is appropriate.

Yes, factor analysis is appropriate for the competence questions because the correlation matrix between all competence variables shows that they are positive correlated and many of them are significantly correlated.

Table 4 below provides the correlation matrix between all competence variables.

	Competence1	Competence2	Competence3	Competence4	Competence5	Competence6	Competence7	Competence8	Competence9	Competence10
Competence1	1.00	0.49	0.38	0.41	0.43	0.36	0.34	0.26	0.49	0.43
Competence2	0.49	1.00	0.52	0.37	0.42	0.32	0.42	0.29	0.43	0.35
Competence3	0.38	0.52	1.00	0.41	0.41	0.30	0.36	0.24	0.36	0.35
Competence4	0.41	0.37	0.41	1.00	0.71	0.42	0.47	0.21	0.32	0.27
Competence5	0.43	0.42	0.41	0.71	1.00	0.50	0.45	0.28	0.36	0.30
Competence6	0.36	0.32	0.30	0.42	0.50	1.00	0.37	0.26	0.32	0.33
Competence7	0.34	0.42	0.36	0.47	0.45	0.37	1.00	0.38	0.34	0.29
Competence8	0.26	0.29	0.24	0.21	0.28	0.26	0.38	1.00	0.32	0.30
Competence9	0.49	0.43	0.36	0.32	0.36	0.32	0.34	0.32	1.00	0.62
Competence10	0.43	0.35	0.35	0.27	0.30	0.33	0.29	0.30	0.62	1.00

Table 4. Correlation Matrix of Competence variables

14. Make a scree plot. How many factors does the scree plot suggest?

The curve in the scree plot takes a sharp turn at index = 2, hence, as per elbow rule, the first 2 factors would qualify. The scree plot is as follows:

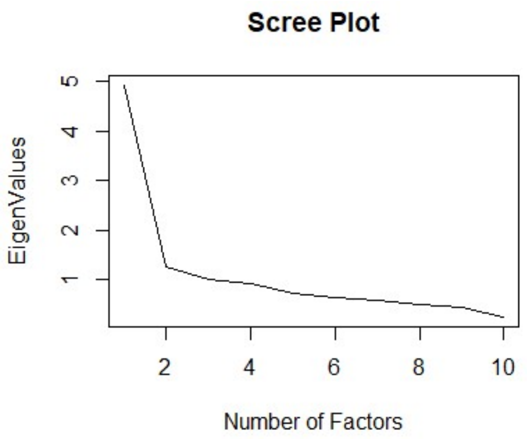


Figure 6 Eigenvalue Plot for Scree Test

15. For what purpose is a rotation of the factors in an exploratory factor analysis used? Should we perform a rotation in this setting? Why or why not?

Factor rotation is carried out to improve the interpretability (to clearly understand which variable(s) relates to which factor) of factors by maximizing the loading of each variable on one of the factors while minimizing the loading on the other factor(s). Here we carry out factor rotation as some of the variables are hard to interpret and loadings obtained after varimax rotation are easier to discern; in fact, it is common to use rotation in practice (Hair, et.al, 2014). In this

	Without Rotation		**With varimax rotation**	
	Factor1	Factor2	Factor1	Factor2
Competence1	0.64		0.39	0.53
Competence2	0.61		0.4	0.48
Competence3	0.58		0.42	0.4
Competence4	0.74	-0.36	0.8	
Competence5	0.78	-0.34	0.82	0.23
Competence6	0.58		0.49	0.31
Competence7	0.60		0.5	0.33
Competence8	0.41		0.24	0.37
Competence9	0.65	0.47	0.21	0.77
Competence10	0.58	0.47	0.73	

Table 5. Comparison of Factor Loadings with and without Rotation

16. Perform factor analysis using the number of factors as suggested by the scree plot. Clearly state how many factors you have included and whether or not you have used a rotation. Report the estimated uniquenesses and factor loadings.

The scree plot flattens at index = 2 and as per elbow rule 2 factors are considered, even though p-value rejects the hypothesis that 2 factors are sufficient (in this case 2 factors were used since the question suggests to use the scree plot analysis).

'Varimax' rotation was used to have a better interpretation and have a better groupings/clusters. The report is as follows:

Uniquenesses

Competence1	Competence2	Competence3	Competence4	Competence5	Competence6	Competence7	Competence8	Competence9	Competence10
0.57	0.61	0.66	0.33	0.28	0.66	0.64	0.81	0.36	0.45

Table 6. Uniquenesses of Competence variables after performing factor analysis

Loadings		
	Factor 1	Factor 2
Competence1	0.39	0.53
Competence2	0.40	0.48
Competence3	0.42	0.40
Competence4	0.80	
Competence5	0.82	0.23
Competence6	0.49	0.31
Competence7	0.50	0.33
Competence8	0.24	0.37
Competence9	0.21	0.77
Competence10		0.73

Table 7. Factor Loadings of Competence variables on Factors
(Factor Loadings less than 0.20 has not been printed)

```
Test of the hypothesis that 2 factors are sufficient.
The chi square statistic is 186.03 on 26 degrees of freedom.
The p-value is 4.04e-26
```

17. Check whether all the variables should be retained in the factor analysis.

a) (a) Which criterion do you use? Which of the variables, if any, should be dropped?

Uniqueness of more than 0.8 can be dropped as a rule-of-thumb. Hence, competence8 was dropped off since its value is 0.81.

b) If one or more of the variables should be dropped, redo the scree plot and the estimation of the factor model with the number of factors suggested by the scree plot. Report and motivate all the steps you have taken to arrive at a final factor model. Report the set of included variables, the estimated uniquenesses and factor loadings of your final factor model.

Competence8 was dropped and scree plot was recreated. Number of factors suggested was still 2.

Factor analysis was carried out on all variables (except competence8) and the convergence test returned TRUE- a measure of appropriateness of the test. The estimation, now provides adequate information on factor loadings and uniqueness of remaining measured variables. No other variable needs to be dropped as the uniquenesses are < 0.8.

Chi-Square test suggests having 5 factors, however, factor loading at factor = 3,4 &5 results in just one variable being loaded to respective factors which goes against the factor model specification, which states that factors are common drivers of variables, hence, we settle with 2 factors as was already determined after scree plot analysis.

Final Factor model is as follows:
Factor 1: Competence 3, 4, 5, 6, 7
Factor 2: Competence 1, 2, 9, 10

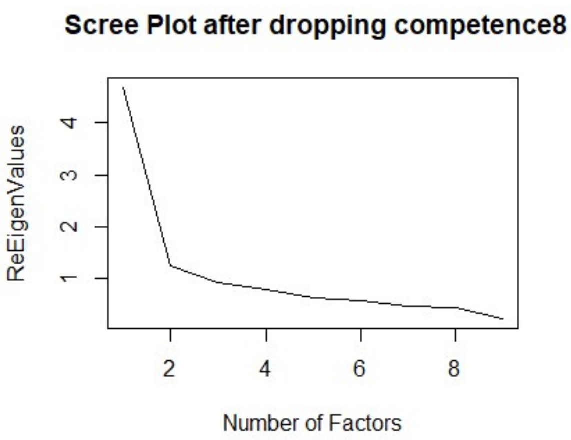


Figure 7. Scree plot after dropping Competence8

Uniquenesses								
Competence1	**Competence2**	**Competence3**	**Competence4**	**Competence5**	**Competence6**	**Competence7**	**Competence9**	**Competence10**
0.56	0.61	0.66	0.33	0.28	0.66	0.65	0.36	0.45

Table 8. Uniquenesses of Competence variables after dropping Competence8 from analysis

Loadings after dropping Competence 8		
	Factor 1	**Factor 2**
Competence1	0.40	0.53
Competence2	0.40	0.47
Competence3	0.43	0.40
Competence4	0.80	
Competence5	0.82	0.22
Competence6	0.50	0.30
Competence7	0.51	0.31
Competence9	0.22	0.77
Competence10		0.73

Table 9. Factor-Loading Matrix of Competence variables after dropping Competence8 from analysis (Factor Loadings less than 0.20 has not been printed)

18. Which names do you suggest for the factors? Motivate the names you have chosen

Factor Labels	Variable (Survey Item)	Motivation
Factor 1 - **Employee engagement**	**Competence3** Scope for development via 'trial and error' **Competence4** Strong individual responsibility of employees **Competence5** Creativity of employees **Competence6** Incentive schemes for employees to innovate **Competence7** Internal co-operation between departments / firm units	These variables potentially represent internal aspects of an organization i.e. how much does an employee align with the company's strategy to innovate
Factor 2 - **Responsiveness to innovations**	**Competence1** Detecting new client's needs **Competence2** Development of new technical solutions **Competence9** Quick implementation of new ideas to the point of market launch **Competence10** Quick imitation of competitor's innovations	This factor represents how quickly the company responds to its client's needs and how adaptable and flexible it is to external demands and ever-changing product/service landscape

Table 10. Factor labels defined based on the factor loadings and appropriateness of representation

19. Perform a reliability analysis of each factor.

a) Which criterion do you use? Which of the variables, if any, should be dropped?

We use Cronbach's alpha to determine the reliability of the factors and their representation of the construct. In our analysis raw alpha = 0.79 and 0.78 for factor 1 and factor 2 respectively. These values cannot be further increased by dropping one or more measured variables, hence, we do not drop any variables from the constructs.

Factor	**Variables**	**Cronbach's alpha**	**Raw_alpha when this item is dropped**
1	Competence 3	0.79	0.78
	Competence 4		0.72
	Competence 5		0.71
	Competence 6		0.77
	Competence 7		0.76
2	Competence 1	0.78	0.72
	Competence 2		0.76
	Competence 9		0.68
	Competence 10		0.72

Table 11. Measure of reliability through Cronbach's α

b) If one or more of the variables should be dropped, redo the scree plot and the estimation of the factor model with the number of factors suggested by the scree plot. Report and motivate all the steps you have taken to arrive at a final factor model. Report the set of included variables, the estimated uniquenesses and factor loadings of your final factor model.

No variable is dropped. Hence, our factor model remains the same.

20. Perform a validity analysis of the factor model by splitting the sample in two random partitions and comparing the factor loadings. Report the estimated uniquenesses and factor loadings of the split samples. What do you conclude?

Although the factor loadings are not the same, the variables are loading onto the same sets of factors in the factor analysis of both the split samples. The table below provides the results with uniquenesses and loading factors after dropping Competence8 which had a uniqueness > 0.8 in the split samples as well. Hence, it can be concluded that the test done for the whole sample holds good for part of the sample and would be representative of a similar bigger sample as well.

	Split-Sample 1			Split-Sample 2		
Variable	Uniquenesses	Varimax-Rotated Loadings		Uniquenesses	Varimax-Rotated Loadings	
		Factor 1	Factor 2		Factor 1	Factor 2
Competence1	0.55	0.42	0.53	0.57	0.37	0.53
Competence2	0.65	0.39	0.45	0.57	0.42	0.5
Competence3	0.68	0.43	0.37	0.64	0.43	0.41
Competence4	0.31	0.81	0.2	0.34	0.8	
Competence5	0.29	0.81	0.23	0.26	0.84	0.21
Competence6	0.65	0.53	0.27	0.67	0.47	0.33
Competence7	0.65	0.49	0.32	0.65	0.52	0.29
Competence9	0.29		0.82	0.40	0.24	0.74
Competence10	0.46	0.23	0.7	0.43		0.74

Table 12. Validation of factor analysis by Split-Sample Estimation
Factor Loadings less than 0.20 has not been printed

21. Summarize and report the results of the factor analysis.

Exploratory factor analysis began with creating a correlation matrix of all the measured variables, which gave us a general idea of correlations between variables and loosely validated our decision to perform EFA. We then moved ahead with creating a scree plot and doing chi-squared tests to decide a best suited number to represent factors on which variables could be modeled and loaded to, while 5 what was suggested by the latter, it was decided that 2 would indeed be sufficient to describe and model the variables and their loadings. Factor analysis carried thereafter highlighted a high uniqueness of competence 8, which was consequently dropped from our model and variables were clearly loaded on to their respective factors. The model thus obtained converged and further verified this analysis. A Cronbach alpha test was then carried out to determine the reliability of the factors and their representation of the construct and to identify a potential need to drop more variables. Further, a validity analysis was done to validate the robustness and scalability of the data. Finally, a scatter plot of the two factors shows no correlation (correlation=0.14) corroborating that these factors are two distinct dimensions of innovation strategy. Here is a table that summarizes 2 factor construct and its interpretation.

Figure 8. Scatterplot of factors Employee Engagement versus Responsiveness to innovations

Variable	Statement	Factor Loadings	
		Factor 1 – Employee engagement	Factor 2 - Responsiveness to innovations
Competence1	Detecting new client's needs	0.40	**0.53**
Competence2	Development of new technical solutions	0.40	**0.47**
Competence3	Scope for development via 'trial and error'	**0.43**	0.40
Competence4	Strong individual responsibility of employees	**0.80**	
Competence5	Creativity of employees	**0.82**	0.22
Competence6	Incentive schemes for employees to innovate	**0.50**	0.30
Competence7	Internal co-operation between departments / firm units	**0.51**	0.31
Competence9	Quick implementation of new ideas to the point of market launch	0.22	**0.77**
Competence10	Quick imitation of competitor's innovations		**0.73**
	Cronbach's α	0.79	0.78
	Proportion of Variance explained	0.27	0.23

Table 13. Results of Factor Analysis

Note: Factor Loadings less than 0.20 has not been printed

22. What type of variables are the estimated factors? Choose from nominal scale, ordinal scale, interval scale or ratio scale and explain your answer.

Estimated factors can be categorized as metric variables of type – "Interval" as the numeric difference between them does not absolute significance. Moreover, there is no absolute zero (meaningful) and it is not possible to perform operations such as division and multiplication.

23. Do enterprises that launch new to market innovations perform better or worse than enterprises that do not launch new to market innovations in terms of the factors that you have identified? Support your answer by a plot and by a t-test.

The boxplots in figures 9 and 10 illustrate how enterprises perform depending on them launching new to market innovations. Here, 0 denotes having no new to market innovation launches, 1 refers to having launched new to market innovations.

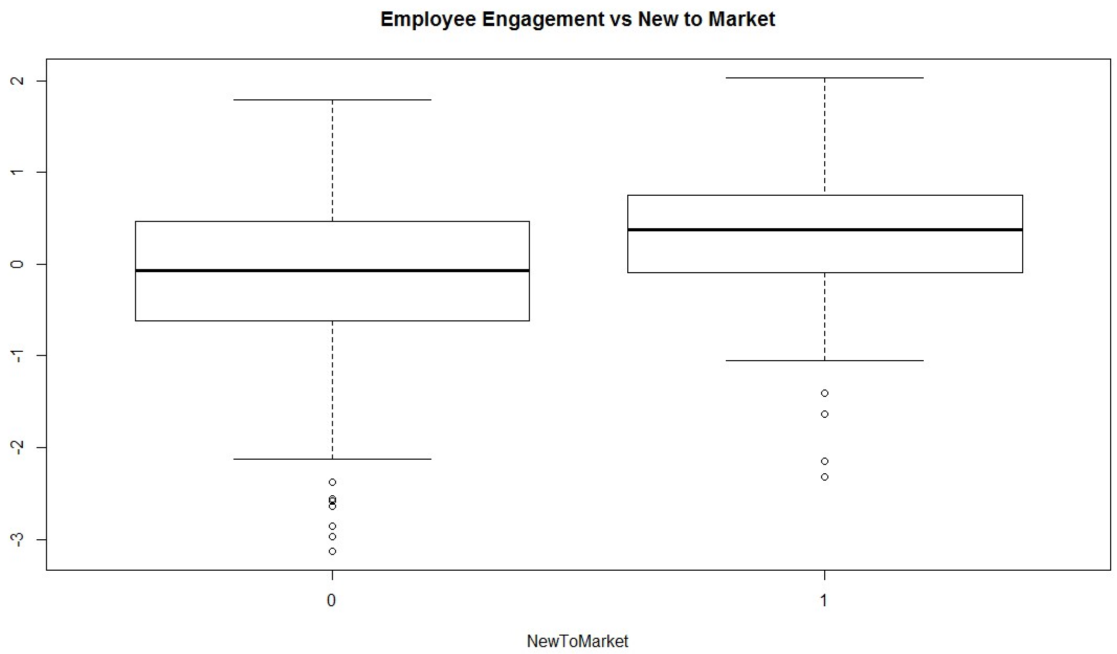


Figure 9. Boxplot showing the relation between the Employee Engagement (first factor) and new to market launches

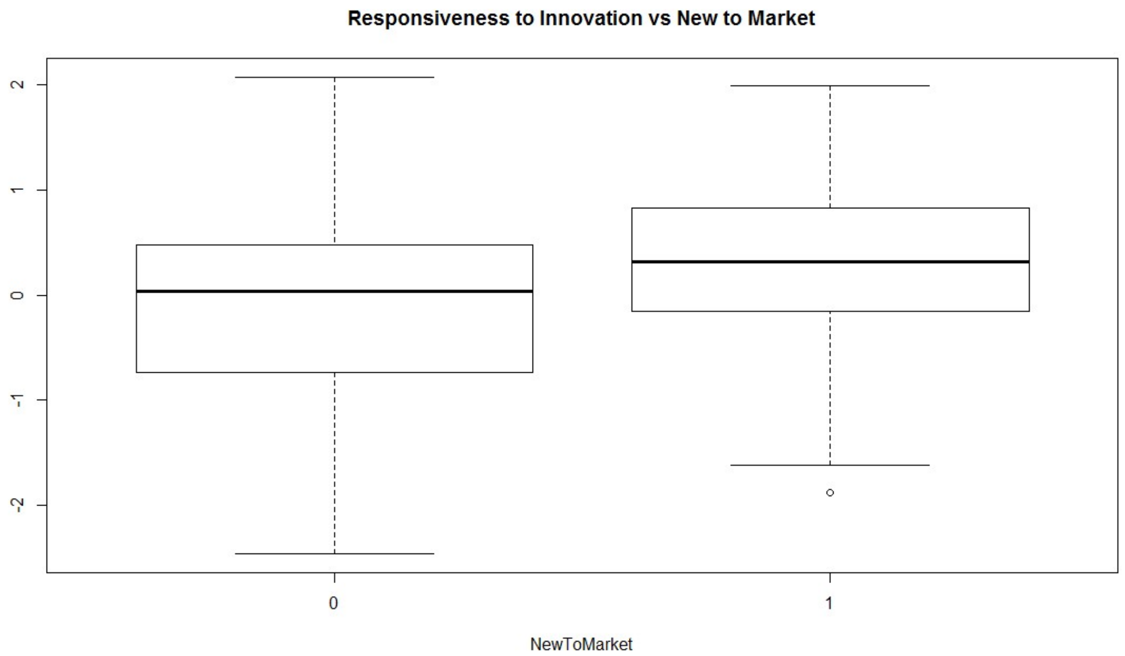


Figure 10. Boxplot showing the relation between responsiveness to innovation (second factor) and new to market launches

Looking at the boxplots, it seems that enterprises that launch new to market innovations have higher scores in terms of the factors that have been identified.

In order to statistically verify the findings based on the boxplots, a t-test is performed. The hypotheses are as below:

$H_0 : Enterprises\ that\ have\ launched\ new\ to\ market\ innovations\ score\ the\ same\ as\ enterprises$
$with\ no\ new\ to\ market\ innovations$

$H_a : Enterprises\ that\ have\ launched\ new\ to\ market\ innovations\ score\ significantly\ different\ than$
$enterprises\ with\ no\ new\ to\ market\ innovations$

The results of the t-test for Employee Engagement (Factor 1) are as follows:

Paired T-Test: $CI_{95\%} = [-0.62\ , -0.39]$

The p-value (< 2.2e-16) shows that the null hypothesis is to be rejected and it is concluded that there is a significant difference between enterprises that launch new to market innovations and those that do not, in terms of Employee Engagement (Factor 1).

The results of the t-test for Responsiveness to Innovation (Factor 2) are as follows:

Paired T-Test: $CI_{95\%} = [-0.57\ , -0.35]$

The p-value (= 6.95e-16) shows that the null hypothesis is to be rejected and it is concluded that there is a significant difference between enterprises that launch new to market innovations and those that do not, in terms of Responsiveness to Innovation (Factor 2).

As a result of the analysis it can be concluded that enterprises that launch new to market innovations perform better than enterprises that do not launch new to market innovations. This is the case for both factors: Employee Engagement (Factor 1) and Responsiveness to Innovation (Factor 2).

24. Do enterprises that have a strictly positive margin (i.e. they have indicated in the survey that the margin is more than 0%) perform better or worse than enterprises with a negative or zero-margin in terms of the factors that you have identified? Support your answer by a plot and by a t-test.

For this question, a new variable was created: Positive Margin. The boxplots in figures 11 and 12 illustrate how enterprises perform depending on them having a positive margin. Here, 0 denotes having a negative margin, 1 refers to having a positive margin.

Figure 11. Boxplot showing the relation between Employee Engagement (first factor) and positive margin

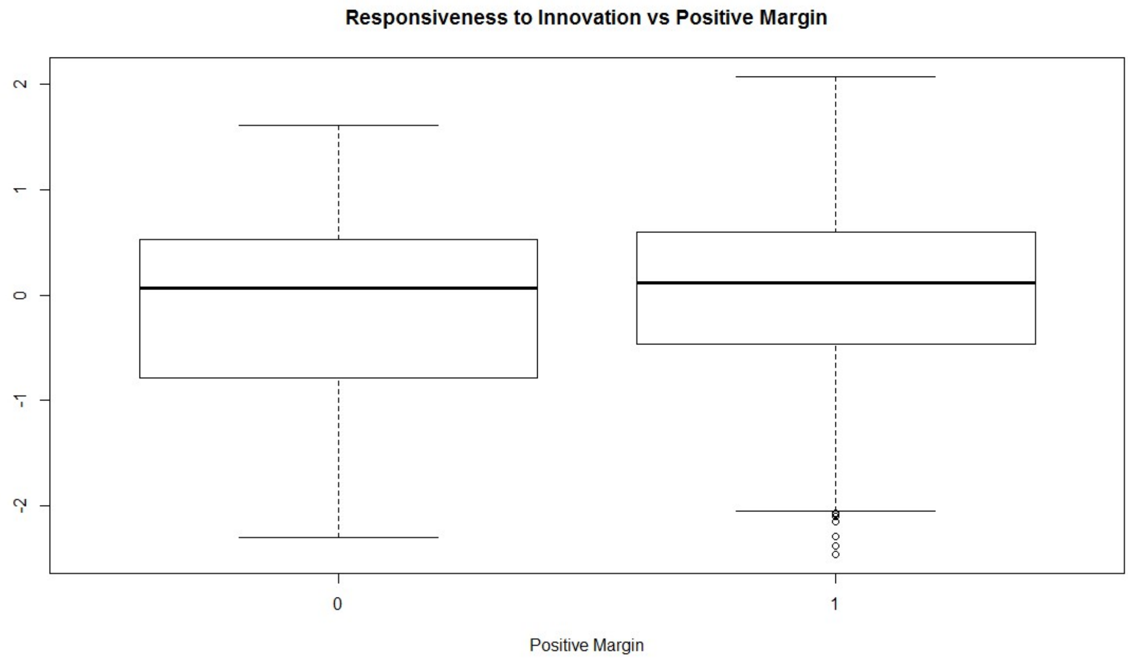


Figure 12. Boxplot showing the relation between the Responsiveness Innovation (second factor) and positive margin

Looking at the boxplots, no clear difference can be spotted for Employee Engagement (Factor 1). For Responsiveness to Innovation (Factor 2), it looks like enterprises with a positive margin perform slightly better than enterprises with a negative margin.

In order to verify the findings based on the boxplots, a t-test is performed. The hypotheses are as below:

$H_0: Enterprises\ with\ a\ positive\ margin\ score\ the\ same\ as\ enterprises\ with\ a\ negative\ margin$

$H_a: Enterprises\ with\ a\ positive\ margin\ score\ significantly\ different\ than\ enterprises\ with\ a\ negative\ margin$

The results of the t-test for Employee Engagement (Factor 1) are as follows:

Paired T-Test: $CI_{95\%} = [-0.31\ , 0.05]$

The p-value (= 0.16) shows that the null hypothesis cannot be rejected and it is concluded that there is no significant difference between enterprises that launch new to market innovations and those that do not, in terms of Employee Engagement (Factor 1).

The results of the t-test for Responsiveness to Innovation (Factor 2) are as followed:

Paired T-Test: $CI_{95\%} = [-0.33\ , -0.001]$

The p-value (= 0.049) shows that the null hypothesis is to be rejected and it is concluded that there is a significant difference between enterprises that launch new to market innovations and those that do not, in terms of Responsiveness to Innovation (Factor 2). The p-value is very close to 0.05 however, looking at the confidence interval, a difference of zero is just outside of the 95% confidence interval.

As a result of the analysis it cannot be concluded that enterprises that has a positive margin perform better than enterprises that do not have a positive margin. This is the case for Employee Engagement (Factor 1). Enterprises with a positive margin do perform better in terms of Responsiveness to Innovation (Factor 2).

25. Do firms with a higher percentage of their turnover attributed to newly introduced or significantly improved products or services perform better or worse in terms of the factors that you have identified?

For this question, t-tests for each pair of consecutive values of InnovTurnoverP are done. The results of these tests can be found in table 13. The hypotheses are as below:

$H_0: Enterprises\ with\ a$ higher percentage of their turnover attributed to newly introduced or significantly improved products or services perform the same than enterprises with a lower percentage

$H_a: Enterprises\ with\ a$ higher percentage of their turnover attributed to newly introduced or significantly improved products or services perform significantly different than enterprises with a lower percentage

	Employee Engagement			Responsiveness to Innovation		
Pair	P-Value	CI-low	CI-high	P-Value	CI-low	CI-high
1-2	2.92e-5	-0.61	-0.23	4.16e-4	-0.52	-0.15
2-3	0.27	-0.09	0.33	0.03	-0.49	-0.03
3-4	0.15	-0.48	0.07	0.74	-0.21	0.3
4-5	0.85	-0.31	0.26	0.51	-0.16	0.31
5-6	0.67	-0.17	0.27	0.004	-0.47	-0.09
6-7	0.15	-0.51	0.08	0.96	-0.21	0.2
7-8	0.95	-0.34	0.37	0.65	-0.2	0.31

Table 13. Results of t-tests of pairs of InnovTurnoverP.

** CI-low and CI-high are the lower and upper bounds of the 95% confidence interval*

From the results in table 13, the following can be concluded. For pair 1-2, the null hypothesis for both factors has to be rejected. Enterprises with a score of 2 for InnovTurnoverP perform better[3] than enterprises with a score of 1. This is the case for Employee Engagement (Factor 1), as well as Responsiveness to Innovation (Factor 2).

For Employee Engagement (Factor 1), the p-values are as such that no further null hypotheses can be rejected. So for all the other pairs, there is no significant difference.

For Responsiveness to Innovation (Factor 2) however, there is a significant difference for pairs 2-3 and 5-6. Enterprises with a score of 3 for InnovTurnoverP perform better than enterprises with a score of 2. And enterprises with a score of 6 for InnovTurnoverP perform better than enterprises with a score of 5.

[3] Performing better in this case is to has more turnover

All in all, for Employee Engagement (Factor 1), any enterprise with a score of 2 or higher performs better than an enterprise with a score of 1. There are no significant differences between the enterprises with a score of 2 or higher.

For Responsiveness to Innovation (Factor 2), Enterprises with a score of 6 or higher perform better than enterprises with lower scores. There are no significant differences between these enterprises. Enterprises with a score between 3 and 5 score better than enterprises with scores of 1 and 2, but perform worse than enterprises with a score of 6 or higher. There are no significant differences between the enterprises with scores between 3 and 5. Enterprises with a score of 2 perform better than enterprises with a score of 1, but perform worse than enterprises with a score of 3 or higher. And finally, enterprises with a score of 1 for InnovTurnoverP perform worse than enterprises with a score of 2 or higher.

26. What do you conclude about competence management in relation to the innovation strategy and business performance from your answer to the previous two questions?

Looking back at the previous 2 questions, it was observed that effects of having higher Employee engagement were insignificant in producing better margins and turnover from launching newly introduced products or services, however an organization's responsiveness to innovation had a positive effect on margins as well as turnover from new products and services. Hence, while these 2 factors should not be considered complimentary, responsiveness to innovation does hold more weight if the focus is on gaining margins and turnovers.

In general, managers should focus more on Responsiveness to Innovation (Factor 2) than in Employee Engagement (Factor 1) because the study shows that focusing in responsiveness will lead the enterprise to perform better in margin (higher margin) and perform better in some levels of innovation turnover (more turnover).

References

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