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THE IMPORTANCE AND ESSENTIAL STEPS OF PILOT TESTING IN MANAGEMENT STUDIES: A QUANTITATIVE SURVEY RESULTS

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Abstract
Pilot testing is the most appropriate tool and play indispensable role while conducting large scale survey to increase the reliability, validity and practicability of the questionnaire, especially in management, social sciences and education studies. Although there are several widely adopted rules of thumb regarding the respondents of pilot testing in respective circumstances like 'How to conduct and whom to include in the sample?' is one of the most frequently asked questions in survey research. The prime aim of this study is to provide clear guidelines for future researchers to increase their research reliability. In the first phase we have reviewed and discussed different pilot studies. Secondly, we reviewed the suggested and adopted rules related to pilot testing. In the last, we present the findings/guidelines based on analysis of the different studies. This step ~~to~~ by step guideline~~s~~ does not provide only researchers the basic understanding of how to conduct pilot testing but also enhances their understanding regarding the importance of the validity and reliability of their studies.

Keywords: Pilot Test, Instrument Validity, Normality, Reliability, Exploratory Factor Analysis, Descriptive Statistics

1.1 Validity of the research instruments

Researcher performed the construct and face validities for the research instruments. For construct validity of academics, researcher sent the questionnaire to 8 different faculty members (Assistant professor/Senior Lecturer level in the fields of management) of Universiti Tun Hussein Onn Malaysia, UTM, University of Buner and UniKL. The researcher received feedback from five of the eight experts. It helped the researcher to finalize the instruments of the study.

For the face validity, the researcher sent the questionnaire to the English language experts, one was a Head of the Department of English and the other was Lecturer. The feedback was incorporated in the research questionnaire. The expert validity of the questionnaire was done with academics and language experts and pilot survey test was performed as per industrial experts and reliability, normality and factorability were performed in pilot testing. PLS was used for convergent and discriminant validity of the constructs.

Experts mainly advised to change some demographic questions or add some and also advised to remove double barrel and unwanted questions, for example, the question about demographics 'manager to management', 'experience to working experience' and 'qualification to academic qualification'. Another change was in the main questionnaire where the expert asked to change organization to company and remove the word competitors.

Additionally, experts also suggested removing some parts from the study. They also advised to rephrase some questions for the main construct of the study. For example, 'my organization has a culture where creativity and innovation is highly regarded' has a double meaning. They advised to change it to a sentence which is clear in meaning. Finally, the research questionnaires were retrieved from the experts. The construct and face validity allow the researcher to proceed to next step of collecting the data for pilot survey. The forthcoming section is about the pilot study and discusses in detail the pilot survey results.

1.2 Pilot test result

The importance of pilot test in questionnaire survey research design cannot be overemphasized. This is the fact that getting the wordings of the questionnaire correctly and pretesting is crucial to the success of the research in general (Cohen, Manion, & Morrison, 2013). The main goals of pilot testing according to Cohen et al., (2013), are to increase the reliability, validity and practibility of the questionnaire. Piloting involves the administration of the questionnaire to a number of respondents who are a representative of the target research sample and the subsequent use of statistical analysis and feedback to reduce the number of items in the questionnaire into manageable number. Cohen et al., (2013), highlighted that the pilot data obtained from pilot test is analyzed to determine the following aspects of statistics:

1) Reliability;
2) Collinearity;

3) Multiple regression and ;
4) Factor analysis.

The fact that majority of the constructs included in the questionnaire were an adaptation from previous studies underlies the need for pilot testing the questionnaire. The aim was to establish the reliability of the different constructs and the items measuring them. The present research identifies collinearity issues, and the factorability of the data through reliability analysis, normality test and factor analysis. This becomes essential to mention that the wordings of the items that measured the respective constructs were modified from their original form in order to suit the context of the present research. The results of the pilot testing will be presented in the forthcoming sections in details.

1.2.1 Demographic profile of respondents

Analysis of the demographic characteristics of the respondents shows that about 51 percent of them were medium companies, while 34 percent indicated that their company has more than 200 employees which means they are considered as large companies and 14 percent revealed themselves as small companies. The gender distribution of the respondents indicated that 69 percent were male while the remaining 31 percent were female. Majority of the respondents indicated that their responsibility were in the top management 44 percent, middle management respondents were 25 percent while lower management staff were 29 percent. The age of company inclination of the respondents showed that 25 percent of the companies aged 12 years, same percentage for the 7 years of establishments, 15 percent for 10 years and 21 percent of the respondent's companies have 15 years of establishment. The working experience of the respondents 44 percent of the respondents 8 years, while 37 percent has 10 years, and 17 percent has 5 years of working experience with same companies. The educational background of the respondents showed that more than half (55.5 percent) possessed degree education, 25 percent holds diploma education while 19.5 percent indicated they has master degree education. Majority of the respondents showed that there companies located in Muar 57 percent, 32.5 percent from Batu Pahat and 10.5 percent showed that there companies located in Kluang.

1.3 Normality test

Data normality is an important aspect in both univariate and multivariate analysis. Downplaying this important stage in questionnaire data analysis process exposes the validity and reliability of the research outcome. Even though the present analysis is solely concerned with identifying the factorability and reliability of a pilot data, it is important to examine the normality of the data. Thus, Child, (2006), argued that both univariate and multivariate normality have to be established within a data set before factor analysis is to be performed. Similarly, Field, (2009) reiterated the importance of the absence of univariate and multivariate outliers within a data set in order to achieve reliable results. These underscore the importance of establishing the normality of the pilot data in the present research.

1.3.1 Univariate Normality

In order to make decision on the normality of the data, certain guidelines and rule of thumbs were used. Authors recommended the use of plots (histogram, stem and leaf plot, box plot and Q-Q plot), omnibus statistical tests (Chi-square goodness of fit, Kolmogorov-Smirnov (K-S) test, Shapiro-Wilk and z-test approximations) and the Skewness and Kurtosis measures as approaches to examine the normality of a given data set (Field, 2009; Pallant, 2011; Pituch & Stevens, 2016).

The rule of thumbs applied for the graph or plot approach involve visual examination of the various plots for evidence of data symmetry. For normality to be established in the data the histogram should not deviate significantly from the typical bell-shaped normal probability curve while the Q-Q plot should approximately follow a straight line.

The omnibus statistical test relied on the application of statistical significance testing to establish distributional normality. These methods are, however, regarded as too sensitive to sample size and might lead a researcher to erroneously make a wrong decision about the normality of a given distribution (Field, 2009; Pituch & Stevens, 2016). It is recommended that this approach should be complimented with the visual plot observation in order to avoid committing an error.

The decision rule for establishing univariate normality using skewness and kurtosis measures involves comparing the respective measures to a magnitude of 2 (Pituch & Stevens, 2016). Measures that returned values less than 2 are considered to reflect that the given distribution does not depart significantly from a normal distribution. Alternatively, univariate normality is also established if the values of skewness and kurtosis each lie within ±2 standard errors of the respective measures (Pituch & Stevens, 2016).

Table 1 shows the descriptive statistics of the questionnaire items. The items were grouped together and the respective statistics are presented in the range. The items for each constructs were assessed based on mean, standard deviation, skewness and kurtosis descriptive statistics.

Table **.**:1: Descriptive statistics of the variables
(Researcher, 2019)

Constructs	No.of original items	Mean	Standard deviation	Skewness	Kurtosis
EOIN	7	3.26-4.23	0.746-1.311	0.193-0.622	0.195-1.290
EOPR	6	2.54-3.82	0.910-1.282	0.112-0.612	0.130-1.130
EORT	6	3.45-3.53	0.887-0.953	0.012-0.102	0.723-0.924
EOCA	6	2.72-2.95	0.887-1.312	0.054-0.509	0.560-1.174
EOA	5	2.68-3.66	0.918-1.264	0.012-0.326	0.797-0.938
INBI	6	1.93-3.92	0.724-0.879	0.129-0.499	0.235-1.582
OUTBI	5	2.47-4.01	0.897-1.139	0.013-0.660	0.022-0.901
FP	8	2.89-3.55	0.964-1.278	0.025-0.075	0.904-1.032

As shown in Table 1, both skewness and kurtosis statistics indicated that univariate normality has been achieved across all the items of the questionnaire. Across all the items the highest absolute value for skewness and kurtosis are 0.662 and 1.582 respectively. These values are below the recommended threshold of 2, thus indicative of attainment of univariate normality in the dataset.

1.3.2 Multivariate normality

After examining the univariate normality in the dataset this section discusses the procedure followed to assess the multivariate normality of pilot data. According to Field, (2009) while satisfying univariate normality test in multivariate data analysis is only a necessary condition, ensuring multivariate normality in the data is a sufficient condition. This argument justifies the need to assess multivariate normality in the pilot dataset. A number of tests are available to test the multivariate normality for a given dataset. Following, Hair, Black, Babin, & Anderson, (2010); Pallant, (2011) and Tabachnick & Fidell, (2013), the researcher adopts the Mahalanobis Distance test to establish the multivariate normality assumption in the pilot data. The procedure involves running a multiple regression analysis with one of the independents variables or any other variable in the data file being assigned as the dependent variable in the regression model by specifying the analysis to compute and save the Mahalanobis Distance statistic. The computed Mahalanobis Distance value for each case is then compared with the critical value obtained from Chi-square table using a given degree of freedom at a specified significance level (usually 0.001).

The original theoretical model for this research consist of 5 independent variables, therefore, the degree of freedom for testing the critical value for the Mahalanobis Distance value is 5. Based on the Chi-square table, the critical value for 5 degree of freedom at alpha value 0.001 is 20.515. Examination of the saved Mahalanobis Distance value in the data file indicated that the largest value was 16.685 associated with the respondents with the ID 046. The Mahalanobis Distance for the all the respondents fall within 0.782 to 16.685 ranges which is within the acceptable critical value of 20.515. Although, the common practice is to remove outliers from the dataset, in this analysis the researcher did not found any outliers, so this confirms the multivariate normality of the dataset.

1.4 Exploratory factor analysis

Having examined both the univariate and multivariate normality in the dataset, in the forthcoming section the result of the exploratory factor analysis, EFA and the reliability analysis is presented. The purpose of conducting factor analysis is to discover the underlying constructs or dimensions in the dataset (Kline, 1994), while reliability analysis measures the performance of the construct. The EFA was conducted following the five methodological steps explained by (Fabrigar, Wegener, Maccallum, & Strahan, 1999), as shown in Figure 1. These steps involve a series of iterative process that are inter-related to one another.

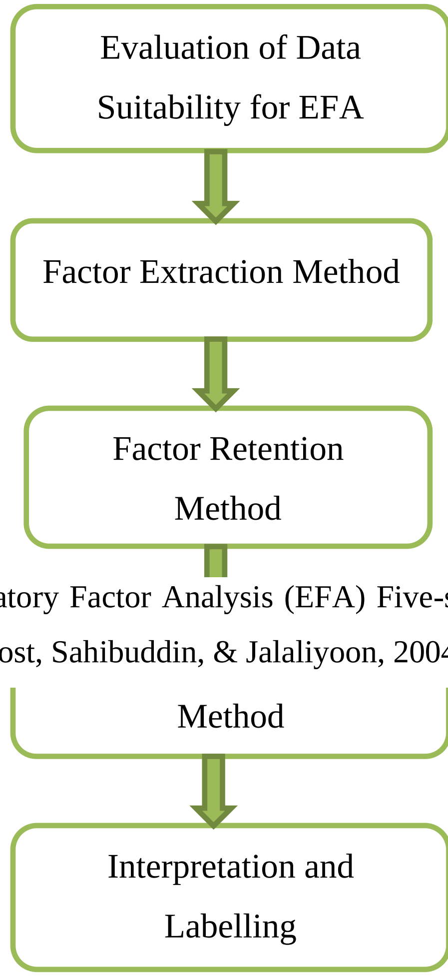

Figure 1: Exploratory Factor Analysis (EFA) Five-step Methodological process (Taherdoost, Sahibuddin, & Jalaliyoon, 2004)

1.4.1 Measuring of sampling adequacy

Ensuring sampling adequacy is one of the important steps in Exploratory Factor Analysis (EFA). There are arguments on what constitute adequate sample when EFA is considered as analytical tool. Some researchers use the minimum number of cases criterion while others are inclined towards cases-to-variable ratio criterion (Beavers et al., 2013). In the case of the minimum number of cases criterion, many rules of thumbs had been advanced. Comrey & Lee, (2013), considered 50 cases as very poor, 100 cases as poor, 200 as fair, 300 as good, 500 as very good and 1000 and above as excellent sample sizes in EFA. Hair et al., (2010), argued that in conducting an EFA the number of observations must be greater than the number of variables and that a sample size of 100 is considered adequate. In respect of the cases-to-items criterion, authors had suggested the ratios of 20:1, 10:1, 5:1 rule of thumbs as the appropriate ratio for the EFA (Costello & Osborne, 2005). However, the ratio criterion had severally been criticized (Beavers et al., 2013). Instead, Guadagnoli & Velicer, (1988), suggested that determining the required sample size in EFA should be based on the strength of the relationship between the factors and the items. Based on this argument, they operationalized the relationship as follows:

(1) If factors have four or more items with loadings of 0.60 or higher, then the size of the sample is not relevant;
(2) If factors have 10 to 12 items that loads moderately (0.40 or higher), then a sample size of 150 or more is required and;
(3) If factors are defined with few variables and have moderate too low loadings, a sample size of at least 300 is needed (Beavers et al., 2013).

Supporting this argument, Fabrigar et al., (1999), indicated that with a sample as low as 100 cases, a stable solution can be obtained when three or four items have higher loadings of 0.70 and above. Therefore, being a pilot survey, a total number of 104 samples were used for this analysis. The number meets the minimum criterion of EFA sample size as recommended by (Hair et al., 2010).

The suitability of the dataset for EFA was evaluated by examining the correlation matrix of the variables, the Kaiser-Mayer-Olkin (KMO). Measures of Sampling Adequacy and the Bartlett's Test of Sphericity as recommended in previous studies (Williams, Onsman, & Brown, 2010). The decision rule applied in assessing the correlation matrix is to examine the determinant. A non-zero determinant indicates that, at least, a factor can be extracted from the dataset (Beavers et al., 2013). On the other hand, best practice among researchers recommends the KMO value to be greater than 0.50 while Bartlett's Test statistic should be less than 0.05 (Leech, Barrett, & Morgan, 2005; Pallant, 2011; Williams et al., 2010).

Table 2 shows the determinant, KMO and the Bartlett's statistics from the analysis. As revealed by the result, the determinant of the correlation matrix is 3.286E-14 which is no-zero, thus indicating that, at least, one factor can be extracted from the dataset. To test whether this value is statistically different from a zero at p=0.05, the Bartlett's Test of Sphericity is required. The result confirmed that the determinant is statistically different from zero (p=.000). The KMO returned a value of .814 which also falls within recommended threshold. Based on these criteria it can be concluded that the dataset is suitable for conducting Exploratory Factor Analysis (EFA).

Table 2: Determinant, Kaiser-Mayer-Olkin and Bartlett's Test of sampling adequacy

Determinant		1.754E-14
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.810
Bartlett's Test of Sphericity	Approx. Chi-Square	10341.749
	df	820
	Sig.	.000

1.4.2 Factor extraction

Having established the factorability of the dataset, the next step in the factor analytical process is to determine the factor extraction method. Factor extraction method involves the task of choosing the most suitable factor analysis method from series of alternative methods to ensure the choice of an optimum method that explains the dataset substianlly. There are various factor extraction methods from which a researcher can choose when conducting factor analysis: Principal Components Analysis (PCA); Principal Axis Factoring (PAF); Maximum Likelihood (ML); Alpha Factoring etc. with each having its own peculiarity and requirements. The PCA and the PAF were identified as the most widely used methods among all the methods (Williams et al., 2010). However, there are arguments whether PCA is actually a factor analysis technique or not. For instance, Costello & Osborne, (2005), argued that PCA is a mere data reduction technique and it not suitable when the goal of analysis is to detect structure or pattern within a given dataset. On the other hand, PAF is considered the suitable factor analysis technique when the goal is to detect the underlying latent construct from many variables. Nevertheless, other believed that the results of the two converges (Thompson, 2007; Velicer, Peacock, & Douglas, 1982). In this regard it was advocated that the researcher should apply both methods so that the best result that are accurately depicts the research goal is chosen (Beavers et al., 2013).

Considering these explanations, the PAF method was chosen as the extraction method in this research. The choice of this method was informed by the fact that the main goal of conducting the factor analysis is to identify the underlying constructs that best represent the original variables in the dataset. Identifying the latent constructs will provide a manageable representative data without substantially losing the inherent characteristics of the original data.

The extraction follows an iterative procedure where the analysis was conducted 17-times before arriving at a simple solution. The process was conducted by using the PAF method with Direct-Oblimin rotation option (Direct-Oblimin attempts to simplify the structure & mathematics of the output) (Yong & Pearce, 2013). Other specifications involve the suppression of factor loadings to .40 such that only variables that load .40 or higher would appear in the output. This was based on the recommendation of Yong & Pearce, (2013), who suggested that factor loadings can be suppressed to as high, as .40. A total number of 8 variables that either substantially cross-loaded or were freestanding (not loading on any factor) were removed from the analysis. Table 4 shows the 8 extracted factors that resulted from the analysis.

1.4.3 Factor retention criteria

The initial extraction of factors analysis displays results with as many factors as the number of variables in the dataset. However, only a few factors would be considered for retention for further analysis and interpretation.

Different criteria have been devised to guide the researcher in making the decision about the number of factors to be retained from factor analysis (Fabrigar et al., 1999). Researcher often resort to the use of Kaiser Criterion, scree plot test, variance extracted, or parallel analysis criterion when making a decision on the number of factors to be retained (Beavers et al., 2013; Fabrigar et al., 1999).

The Kaiser Criterion has been identified as the most widely used method among researchers (Beavers et al., 2013; Costello & Osborne, 2005). It involves computing the eigenvalues for the correlation matrix of the dataset to determine how many of these eigenvalues are greater than 1 which is then used as the cut-off point for the number of factors to be retained (Fabrigar et al., 1999). However, the method has been criticized as being too arbitrary and it is prone to over-factoring and/or under-factoring as the case may be (Beavers et al., 2013; Costello & Osborne, 2005).

The scree plot test involves plotting a graph of the eigenvalues and then examining it to identify the point at which the bend breaks of flattens out. The number of factors retained is usually determined by the number of data points that occurred above the break-point (Beavers et al., 2013; Costello & Osborne, 2005; Yong & Pearce, 2013). However, identification of the cut-off point that determines the number of extracted factors has been criticized as being subjective (Beavers et al., 2013; Costello & Osborne, 2005). Nonetheless, with the presence of strong common factor the scree plot test is considered to functions well (Fabrigar et al., 1999; Yong & Pearce, 2013).

Another method of determining number of factors to retain is variance extracted method. The criterion involves retaining factors that explains certain percent of extracted variance (Beavers et al., 2013). The decision rule for acceptable percentage benchmark is, however, a subject of debate among researchers. Whereas some suggested as low as 50 percent explained variance as acceptable, other argued that the variance explained should be 75 percent and above (Beavers et al., 2013).

In line with the aforementioned discussion, multiple criteria were used to decide on the number of factors it be retained in the present analysis. This is to ensure the retention of "optimal" number of factors. By using multiple criteria, the risk of substantial data loss as a result of under-factoring was hopefully avoided. In the same vein, the risk of including extraneous factors because of over-factoring was likely avoided too. Factor retention decision was based on scree-plot test and the Kaiser Criterion.

Figure 2 show the scree-plot generated from the data. By visual observation the point where apparent break occurs in the graph is at the point where the blue slant line crosses the green vertical line. This point coincided with the number 8, which represent the 8^{th} factor in the series. Field, (2009) and Williams et al., (2010) explained that factors that occurred above the elbow or point of inflexion should be retained in the scree-plot test. Based on the Figure 2 it is considered that 8 factors can appropriately be extracted for further analysis.

In order to compliment the scree-plot test method, the Kaiser Criterion was also used to determine the number of factors to retain. Table 3 show the eigenvalues of the first 8 factors extracted from the analysis. The total eigenvalue for all the 8 factors were all above 1 which is the Kaiser's benchmark for factor retention. Strictly following the Kaiser Criterion, only 8 factors should be retained. However, (Jolliffe, 1986) cited in Field, (2009), criticized the Kaiser Criterion as being too strict and suggested that factors with eigenvalue as low as 0.70 should also be retained. Following the Kaiser's Criterion for factor retention this research retains only 8 factors.

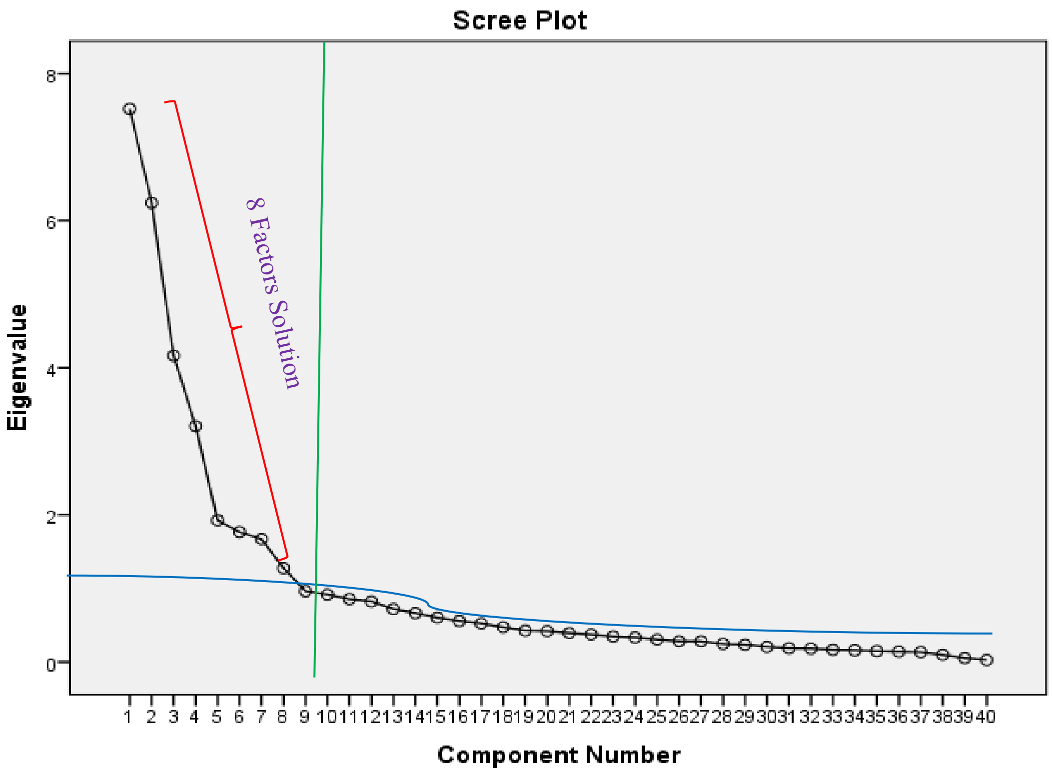

Figure 2: Scree-plot test
(Researcher, 2019)

Table:3: Total Variance Explained
(Researcher, 2019)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums Of Squared Loadings
	Total	%of Variance	Cumulative %	Total	%of Variance	Cumulative %	Total
1	7.598	18.531	18.531	7.227	17.627	17.627	4.148
2	6.287	15.335	33.866	5.932	14.469	32.097	4.048
3	4.225	10.304	44.169	3.864	9.425	41.521	3.764
4	3.227	7.872	52.041	2.876	7.014	48.535	3.620
5	1.932	4.713	56.754	1.584	3.862	52.398	3.260
6	1.846	4.503	61.257	1.397	3.406	55.804	2.253
7	1.662	4.054	65.311	1.294	3.157	58.961	2.215
8	1.314	3.205	68.515	.898	2.189	61.150	1.763

Truncated to show only the 8 extracted factors

1.4.4 Factor rotation method

The next step in the factor analytic process is the choice of rotation method. The main goal of rotation in factor analysis is to simplify and clarifies the structure of the data (Costello & Osborne, 2005). There are different types of rotation that can be performed in factor analysis which broadly categorized into two: orthogonal rotation and oblique rotation. The orthogonal rotation (varimax, equmax, quartimax) is used when no correlation among factors is assumed while oblique rotation (direct oblimin, quartimin and promax) is used when the researcher assumes correlation among the factors (Costello & Osborne, 2005; Fabrigar et al., 1999; Field, 2009). For this analysis, oblique rotation using direct oblimin was used. This decision was made because the observed factor correlation matrix (not reported here) showed that some of the factors were correlated.

1.4.5 Interpretation and labelling of factors

The final step in the factor analysis process is the interpretation and labelling the retained factors. The process involves assigning name for the given factor in order to reflect it theoretical or conceptual meaning it is intended to convey (Taherdoost, Sahibuddin, & Jalaliyoon, 2014). **Table 4** shows the questionnaire items and their loadings on the extracted factors. As shown in **Table 4** the items that loaded highly on factor 1 were statements that express respondents' staff get time for learning during their daily routine, hence the factor can conveniently be labelled "Entrepreneurial Orientation Innovativeness (EOIN)". Four items loaded highly on factor 2. The questions associated with these items asked the respondents a manager takes risks and fails, he/she is not penalized. As shown in the table all six items relate to risk taking, therefore factors were labelled as "risk taking (EORT)". Factor 3 has two items that loaded highly on it. The items related to a question that asked the respondents to indicate the frequency about the emphasis on creating important partnerships with supplier/retailer on a higher level than the competitors. As indicated in the table all five items coincided with aggression, thus the factors were named as "competitive aggressiveness (EOCA)". The fourth factor constitutes of items from a question that test the respondent's frequency about changes happen in the company regularly. All the factors sowed in the table measures proactive-actions, therefore the factors labelled as 'proactiveness (EOPA)'. The items that load on factor five, asked about the financial output, our operating income increases faster. A look at the statements from these items, it can be concluded that they can be conveniently be labelled as 'firm performance (FP)'. Factor number 6 contains four items that dealt with a question, staff members are allowed to deal with problems, with the highest loadings amongst other factors. Examining the statements shows that the items reflect the sole decision of the respondents; hence the factor is labelled as "autonomy (EOA)". The items that load on factor seven belong to the question that measures the respondents' opinion on open innovation. The statement indicated that generally, all technologies are externally commercialized (i.e. sold to outside firms), highly loaded on the same items table, therefore it can be conveniently labelled as 'outbound open innovation (OutbI)'. Other four items that relate to the question that measured the respondents' intention to open innovation on factor 8. Examining the statements highly loaded on factor 8, often brings in externally developed knowledge and/or technology to use in conjunction with our own R&D, shows that it measures the open innovation as well. The statements indicated that the factor can be conveniently labelled as "inbound open innovation (InbI)". **Table 4** shows the factors and the respective items that loaded on them. The factor loadings range from a minimum value .467 associated InbI factor to a maximum of .849 associated with EOIN factor. Similarly, all the reported Sum of Square Loadings (Eigenvalues), are high (1.662- 7.598) which is an indication that the factors are sufficiently explained by the loaded items (Field, 1999).

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Table 4: Rotated Pattern Matrix of Factors
(Researcher, 2019)

Codes	**Factor**						
		EOIN	EORT	EOCA	EOPR	FP	E
EOIN3	Staff get time for learning during their daily routine	.849					
EOIN4	Focus on developing new competencies even if the existing ones are effective	.818					
EOIN2	Management actively seeks and rewards innovative ideas	.767					
EOIN5	Ventures units facilitate and enable new product and service development	.705					
EOIN7	Innovation generate significant new value for our customers	.668					
EOIN6	Open to sourcing of ideas from shared forums and professional groups	.666					
EORT4	A manager takes a risk and fails, he or she is not penalized		.798				
EORT5	There are structure to monitor and manage risk		.770				
EORT3	To make effective changes to our offering we willing to accept moderate level of risk		.742				
EORT1	Innovation is perceived as too risky and is resisted		.706				
EORT6	A number of strategies that helps us to manage and reduce risks		.696				
EORT2	Missing an opportunity in the market is considered as a risk		.682				
EOCA4	Emphasis on creating important partnerships with supplier/retailer, on a higher level, than the competitors			.812			
EOCA2	Emphasis on pushing costs lower, faster than our competitors do			.805			
EOCA1	Places emphasis on beating competitors to enter new market			.779			
Codes	**Factors**						
		EOIN	EORT	EOCA	EOPR	FP	EO
EOCA3	Adequate level of capabilities to compete aggressively			.726			
EOCA5	Find ways to differentiate itself from competitors			.587			
EOPR3	Change in my company happens regularly				.780		
EOPR1	Initiates actions to which competitors respond				.779		
EOPR4	Participates in strategic alliances/ partnerships/ joint ventures with outside companies				.765		
EOPR2	usually leads the market in product and service development				.740		
EOPR6	a strong tendency to be ahead of others in introducing novel ideas				.727		
EOPR5	Staff are encouraged to proactively monitor changes in the environment				.658		
FP6	Our operating income increases faster					.809	
FP2	Our sales grow faster for the last three years					.795	
FP1	The firm has achieved rapid growth					.784	
FP4	Our market share grows faster					.765	
FP3	Employment growth in our company is faster					.552	
EOA1	Staff members are allowed to deal with problems						.7

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EOA2	Operating divisions or sub-divisions are quite independent						.7
EOA3	Staff member to be creative and try different methods to do their job						.6
EOA4	Employees are allowed to make decisions without going through elaborate justification and approval procedures						.4
OutI1	Generally, all technologies are externally commercialized						
OutI5	(i.e. sold to outside firms).						
OutI2	Sells the rights to use internal inventions (e.g. licensing)						
	External technology commercialization is restricted to technologies that are not used internally						
OutI3	External technology commercialization is restricted to relatively mature technologies						
InbI4	Often brings in externally developed knowledge and/or technology to use in conjunction with our own R&D						
InbI5	Seeks out technologies and/or patents from other firms, research groups, or universities						
InbI3	It is good to use external sources (e.g., research groups, universities, suppliers, customers and competitors etc.) to complement our own R&D						
InbI2	Actively seeks out external sources (e.g., research groups, universities, suppliers, customers competitors etc.) of knowledge and/or technology when developing new products						
Sum of Square Loadings (Eigenvalues)		7.598	6.287	4.225	3.227	1.932	1.8
Percentage Variance Explained		17.627	14.469	9.425	7.014	3.882	3.4

EOIN- Entrepreneurial Orientation, Innovativeness, EORT- Entrepreneurial Orientation Risk Taking, EOPR- Entrepreneurial Orientation Proactiveness, EOCA- Entrepreneurial Orientation Competitive Aggressiveness, EOA- Entrepreneurial Orientation Autonomy, FP- Firm Performance, OutI- Outbound Innovation, InbI-Inbound Innovation.

1.5 Reliability analysis

The previous section explained the steps followed in determining the structure of data through the factor analysis process. Having established the number of factors to be retained it is recommended that the reliability of the items and their respective constructs be examined in order to establish the validity of the questionnaire scales. In this section the reliability of the questionnaire scales was tested using the Cronbach's Alpha method. The acceptable threshold for scale reliability is .70 and above although .60 is also regarded as acceptable when the study is at its exploratory stage (Hair et al., 2010). Similarly, another important statistic usually examined is the corrected item-total correlation. This measures the internal consistency of the scale and value of .30 and above is recommended (Field, 2009).

Table 5 shows the result of the reliability analysis. The reported Scale's Cronbach's Alphas indicated that all the scales are reliable. The Risk-Taking scale reported the highest alpha value (α= .905) with corrected item-total correlations ranging from .709 to .808. The next highest alpha values are associated with the Entrepreneurial Orientation Innovativeness (α= .897), Firm Performance (α= .888) and Entrepreneurial Orientation Competitive Aggressiveness (α= .883). The corrected item-total correlations in respect of these scales range from .691 to .780 for EOIN, related to FP and EOCA respectively. The reported alpha values and the corrected item-total correlations of the remaining four scales also satisfy the recommended threshold of .70 and .30 respectively with the lowest reported alpha value and item-total correlation associated with Entrepreneurial Orientation Autonomy and Inbound Open Innovation construct respectively. In general, therefore, it was concluded that the questionnaire scales were reliable and could be useful in measuring what it is intended to measure.

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Table 5: Reliability analysis of the questionnaire scales

Codes	Corrected Item-Total Correlation	Cronbach's Alpha if items Deleted	Scale's Cronbach's Alpha
EOIN3 EOIN4 EOIN2 EOIN5 EOIN7 EOIN6	.731 .780 .742 .702 .691 .702	.878 .870 .876 .882 .883 .883	.897
EOPR3 EOPR1 EOPR4 EOPR2 EOPR6 EOPR5	.702 .629 .682 .718 .636 .705	.847 .857 .849 .842 .856 .847	.872
EORT4 EORT5 EORT3 EORT1 EORT6 EORT2	.731 .722 .730 .808 .737 .709	.890 .891 .890 .878 .889 .893	.905
EOCA4 EOCA2 EOCA1 EOCA3 EOCA5	.713 .767 .713 .778 .702	.863 .857 .861 .854 .864	.883
EOA1 EOA2 EOA3 EOA4	.717 .608 .625 .473	.679 .736 .725 .803	.789
INBI4 INBI5 INBI3 INBI2	.451 .526 .563 .617	.727 .737 .688 .702	.749
OUTBI1 OUTBI5 OUTBI2 OUTBI3	.631 .646 .618 .675	.772 .764 .788 .751	.815
FP6 FP2 FP1 FP4 FP3	.768 .764 .785 .560 .771	.854 .855 .850 .901 .854	.888

1.5 Discussion and Conclusion

The analysis assess the validity, normality, factorability and reliability of the pilot data. The analysis of the pilot data revealed that all the data were normally distributed within the range of skewness and kurtosis scores of +/-2. All the eight constructs of the research were reliable as the reliability test revealed Cronbach's alpha coefficient 'Between' 0.749 to 0.905 all above the recommended threshold. Exploratory Factor analysis of the constructs discovered that all the items have good factor loadings on the constructs and have Eigen values greater than 1 to explain more than 50% variance in each of the constructs. Based on the outcomes of the pilot survey results, the items with problem were looked into and were deleted to reflect the study area very well because some comments were also received with the questionnaire that the items are too many and its effects the answering the items in good manners. The deleted items were then checked again to see the effect of that items on constructs, but no effect were found, that's why that it still remain in that way to reflect the study in good manner. The drafted questionnaire was therefore updated to reflect the observation made. In this research, eight factors have been generated and labeled as; (1) Innovativeness, (2) Risk-Taking, (3) Proactiveness, (4) Autonomy, (5) Competitive Aggressiveness, (6) Inbound Innovation, (7) Outbound Innovation, (8) Firm Performance. In order to evaluate the dimensions of entrepreneurial orientation and also understand its effect on open innovation (inbound & outbound innovation) and firm performance, a conceptual model is developed as it is shown in Figure XX. For future work, it is suggested to apply Structural Equation Modeling (SEM), as a confirmatory approach is used to test the measurement model and the path model simultaneously.

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