A STATISTICAL METHOD FOR ANALYZING DATA FROM NATIONAL SYSTEMS OF INNOVATION SURVEYS.

DANIEL NGARI KIIRITHIO

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DECLARATION

DECLARATION BY THE CANDIDATE

This dissertation is my original work carried out at the University of Nairobi during 2013/2014 academic year and has not been presented for the award of any other degree in any university.

Signature: ……………………………………. Date: …………………………..

Daniel Ngari Kiirithio

DECLARATION BY THE SUPERVISOR

This dissertation has been submitted for the partial fulfillment of the requirements of the degree of Master of Science in Biometry with my approval as the supervisor.

Dr. Nelson Owour
School of Mathematics
University of Nairobi

Signature: ………………………………….. Date: …………………………

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ABBREVIATIONS

EFA	-	Exploratory Factor Analysis
FA	-	Factor Analysis
FOSS	-	Free and Open Source Survey
GNSI	-	Ghana National System of Innovation Survey
H	-	Head
ICT	-	Information and Communication Technology
KBIs	-	Knowledge-Based Institutions
KMO	-	Kaiser-Meyer-Olkin
KNUST	-	Kwame Nkrumah University of Science and Technology
MHTI	-	Medium- and High-Tech Industry
MSA	-	Measure of Sampling Adequacy
NIS	-	National Systems of Innovation
OECD	-	Organization for Economic Co-operation and Development
PAF	-	Principal axis factoring
PCA	-	Principal Component Analysis
R	-	Correlation Matrix
R&D	-	Research and Development
STEPRI	-	Science and Technology Policy Research Institute
SPSS	-	Statistical Package for Social Sciences
SW	-	Shapiro-Wilk
T	-	Tail
UNIDO	-	United Nations Industrial Development Organization

ABSTRACT

A National System of Innovation (NSI) represents the strength and quality of the systematically organized interactions and linkages between Government, Knowledge-Based Institutions (KBIs), Industry and Financial Arbitrageurs. A comprehensive understanding of the factors that affect innovation in the NSI would be crucial in enhancing and promoting innovation as a development asset. The purpose of this paper is to identify the latent factors affecting innovation in NSI. Data used was from Ghana National System of Innovation Survey conducted in 2012.Exploratory factor analysis with principal component analysis extraction method and varimax rotation was used. The analysis produced four latent factors; Poor Human Capital, Regulatory Indiscipline, Undemanding Markets and Regulatory Risks.

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CHAPTER 1: INTRODUCTION

1.1 Background

Innovation is widely recognized by industry and academics as an essential competitive enabler for any enterprise that wants to remain competitive, survive and grow.

Organizations operating under the present conditions of global competition and rapid technological change must innovate in order to grow and survive. Changes in consumer desires, manufacturing technology and information technology are occurring at an increasing pace forcing corporations which do not lead or quickly adapt to these changes to cease to exist (Tushman & Anderson, 1986). Therefore, fostering innovation remains a major challenge for business executives and an area in which academic research can make valuable contributions.

Surveys such as the annual innovation survey from The Boston Consulting Group [1] however, suggest that although the importance of innovation is fully realized by most enterprises and they continue to spend more and more on innovation, many of these initiatives do not generate satisfactory profit or competitive advantage. The problem does not lay in the invention part or the generation of innovative ideas, but more in the successful management of the innovation process from an idea to a successful product in the market.

Piater (1984) has stated that a barrier to innovation is any factor that influences negatively the innovation process. There is a general assumption that an identification and removal of a barrier, will improve partly or completely the innovation process. In accordance with Hadjimanolis thoughts (2003) this is far from true, as removal of a barrier does not automatically guarantee smooth flow of the innovation process.

Barriers to innovation can be classified in different ways and different typologies e.g. origin, source. A useful classification of barriers is made by Piatier (1984); he classifies company's internal and external barriers.

Hadjimanolis (2003) admits that external barriers have their origin in the surrounding environment and cannot be influenced. However, a company can affect internal ones. According to King's (1990) classification there are individual, group, firm, inter-organization and regional/national level barriers.

An identification of barriers can assist in fostering an innovative culture in firms by supporting new ideas or galvanizing proper innovation management. On a national level, it is important to identify and remove barriers in order to foster innovation based competition and do not allow failures to innovation (Woolthuis, 2005; Chaminade et al., 2009).

There are contradictory assumptions regarding new firms: they are expected to participate in innovative activities more than established firms. New firms might be less constrained by risks of cannibalizing existing product portfolios. However, new firms confront barriers to innovation due to a lack of prior expertise and lack of financial resources (Schoonhoven et al., 1990).

Classified parameters of barriers are: identification of a barrier, estimation of its frequency and ranking of importance. Barriers may vary also by sector (Preissl, 1998).

1.2 Statement of Problem

Innovation is becoming a part of public discussions, business forums, and media announcements more often than it did in the past. However, the term 'innovation' carries multiple meanings, and is often used in the narrow context of short-term relevance.

Thus the answer to any question about 'innovativeness' varies considerably, depending on the sector and the context under discussion. Many analysts, business planners, and researchers now recognize that macro indicators—such as national investment in research and development (R&D), the patents filed in a year etc. are inadequate to capture the realities of innovation system. These indicators alone are not sufficient to provide policy makers with the necessary evidence to take concrete actions to stimulate and accelerate innovation in academia and the industry, agriculture, and services sectors. Multiple elements need to be considered in totality in order to address the challenges of innovation.

Innovation studies have extensively examined the drivers and sources of innovation, paying particular attention to the technological and organizational capabilities that firms need to develop to become successful innovators (e.g. Schumpeter, 1950; Dosi, Nelson and Winter, 2002; von Hippel, 1994). This literature, however, has been comparatively less systematic in examining the factors that block innovation or cause innovation failures. Redressing this unbalance is crucial for at least two reasons. On the one hand, from an innovation policy perspective, it is important to identify the entry barriers faced by potentially innovative firms, in order to foster innovation based competition dynamics and attenuate systemic failures to innovation (Woolthuis, 2005; Chaminade etal., 2009).

On the other hand, from an innovation management perspective, It is important to identify the obstacles most commonly faced by firms along their innovative activities, in order to enhance the economic pay-offs from innovation-related efforts (Dougherty, 1992; Ferriani et al., 2008).

1.3 Objectives

The overall objective of this study is to determine the statistical method that can be used to analyze data from national systems of innovation surveys.

The specific objective will be;

- ❖ To identify the factors that affect the national systems of innovation using factor analysis being one of the data reduction techniques.

1.4 Significance of Study

Innovation is the key to the economic development in today's knowledge driven economy. Innovation has experienced a remarkable change in recent years as a consequence of a number of factors including the advance of science and technology and the increasing globalization of a number of markets and activities. The growing heterogeneity of sources affecting the process of firms' innovation has led to the knowledge created out of the companies themselves achieving greater importance, and therefore to the central role to be played by the capacity of integrating inner and outer sources of technological capabilities with other competitive forces.

To become competitive in today's market it needs urgent shift towards a more knowledge-based economy which requires strong innovation system. Hence the need to investigate the factors hindering innovation. This study aims at improving the understanding of the factors that act as obstacles to innovation.

Chapter 2 of this report describes what has been done before in the field of innovation. Chapter 3 describes the methods used to conduct the study. Chapter 4 describes the results of the study and finally chapter 5 concludes on the result and give the necessary recommendations.

CHAPTER 2: LITERATURE REVIEW

Some of the basic ideas behind the concept ‘national systems of innovation’ go back to Friedrich List (List 1841). His concept ‘national systems of production’ took into account a wide set of national institutions including those engaged in education and training as well as infrastructures such as networks for transportation of people and commodities (Freeman 1995). He focused on the development of productive forces rather than on allocation issues. Referring to the ‘national production system’ List pointed to the need for the state to build national infrastructure and institutions in order to promote the accumulation of ‘mental capital’ and use it to spur economic development rather than just to sit back and trust ‘the invisible hand’ to solve all problems.

According to Chris Freeman recollections, the first person to use the expression 'National System of Innovation' was Bengt-Ake Lundvall and he is also the editor of a highly original and thought-provoking book (1992) on this subject. However, as he and his colleagues would be the first to agree (and as Lundvall himself points out) the idea actually goes back at least to Friedrich List's conception of ''The National System of Political Economy' (1841), which might just as well have been called 'The National System of Innovation'.

The main concern of List was with the problem of Germany overtaking England and, for underdeveloped countries (as Germany then was in relation to England), he advocated not only protection of infant industries but a broad range of policies designed to accelerate, or to make possible, industrialization and economic growth. Most of these policies were concerned with learning about new technology and applying it.

At the outset, the NIS approach has been applied to reveal the structure of and the main actors involved in innovation processes in a couple of highly industrialized countries as well as in a smaller number of emerging countries. Typically, these early NIS studies (see Nelson (1993)) did not follow a formalized structure and concentrated at one country at a time. Due to the insights on the distinctive patterns of innovation processes and their determining forces that have been gained in these studies, and due to the realistic assumptions underlying the NIS approach, it disseminated rapidly through the economics of innovation literature.

This has led to the introduction of related but otherwise confined approaches to innovation systems. Consequently, the systemic approach to innovation now consists of various branches. Depending on the chosen level of analysis, the concepts of regional innovation systems (e.g. Braczyk et al. (1998), Ohmae (1995)), sectoral innovation systems (Breschi and Malerba (1997), Malerba (2002), Cooke et al. (1997)) and technological systems (Carlsson (1995, 1997), Carlsson and Stankiewicz (1995)) constitute three alternatives to the concept of national systems. In addition, related concepts like the concept of industrial clusters (e.g. Porter (1998)) have been introduced.

Studies of national systems of innovation are founded on the view that the innovation process of a country as well as of an industry sector depends not only on how the individual institutions (e.g. firms, research institutes, universities) perform in isolation, but on how they interact with each other as elements of collective system of knowledge creation and use, and on their interplay with social institutions (such as values, norms and legal frameworks) (Gu, 1999, OECD, 1997). An understanding of these systems is seen to be an aid to help policy makers develop approaches for enhancing innovative performance.

While a significant amount of international literature is currently emerging on the concept of national systems of innovation, very little of this work has, however, been sector specific – and much of the work has been at a broad macro-level.

Since the pioneering work on the nature of innovation in the 1970s (Gibbons and Johnston, 1974; Freeman, 1974), a substantial literature has developed on the innovation process. This process is now known to be highly systemic and complex, to vary across industry, technology, and with different size of firm. In many ways it is idiosyncratic, as firms individually respond to their particular market and technological challenges. Research in this area points to the importance of managerial factors— in strategy, organizational structure and choices about technology— in determining the sources, nature and outcomes of innovation. All these factors make the innovation process difficult to measure in complete and standardized ways. Given the importance of innovation for national and corporate wealth and welfare, however, assessing the way it can be measured in a manner that can account for these factors is a valuable thing to do. Measurement enables comparisons to be made, and helps identify the need for improvement.

A framework proposed by Neely et al (2001) suggest that the firm's capacity to innovate and innovation itself do not depend upon a company's resources and internal environment, but also on external facilitating factors (business support agencies, public grants, active local business networks etc) which tend to be different in different contexts. In detail the proposed framework is based on the following assumptions:

1. A firm possesses an inherent capacity to innovate, which is embedded in the firm's culture, internal processes and capabilities to understand the external environment.

2. The capacity to innovate of firm affects the innovativeness of the firm in terms of product and process innovation, and also organizational innovation.
3. Even if a firm is highly innovative, it has to exploit its innovations in terms of outcomes – i.e. use them to reduce costs and/or to offer products or services to its customers. This is a condition to gain better business performance, such as market share and financial performance.

The external contextual environment can influence both the firm's capacity to innovate and the innovation itself. On the other hand the following factors are identified as factors inhibiting innovation:

- Innovation is poorly defined because customer requirements are not well understood and therefore the goals are not established properly. This is often because some organizations tend to be internally focused and innovating activity is weighted in terms of economic returns and short- term goals such as profit improvement targets.
- Culture is too inhibitive and as such does not foster innovation as an ongoing activity. Employees are not fully aware of the need to be proactive and innovate, and not necessarily encouraged and motivated to perform using their creative potential. There is lack of involvement, absence of team work, and the thinking that innovation is a management responsibility
- Organizational factors such as attitudes of doing more of the same, rewarding the status quo, poor resource allocation and utilization.

Booz Allen Hamilton [11] found that a common denominator among successful innovators is "a rigorous process for managing innovation, including a disciplined, stage-by-stage approval process combined with regular measurement of every critical factor, ranging from time and money spent to the success of new products in the market."

If a substantial portion of the potentially innovative firms do not invest in innovation related activities, it is plausible to claim that the innovation system is suffering from systemic failures to innovation. Following Chaminade and Edquist (2006) and Chaminade et al. (2008), we define systemic failures to innovation as factors weakening the capabilities of firms to engage in interactive learning and innovation, and therefore, hampering innovation at a system level. Systemic failures to innovation include: a) the lack of private institutional support for innovation, as for instance the
restricted availability of finance for activities that entail high levels of risk and uncertainty; b) the lack of information on technological and market opportunities for

innovation, as a consequence, for instance, of a weak connectivity between organizations in the innovation system; c) the lack of an adequate scientific and research infrastructure, as for instance, the weakness in the supply of an adequate skill-base from secondary and tertiary education; and d) the characteristics associated with the market structure and the potential entry barriers from incumbents; among other factors.

One first indication of the extent to which barriers to innovation are prevalent among firms in a particular system, is provided by the proportion of firms that assess that certain factors have been ‘highly important’ in hampering their innovation activities or shaping their decision of not engaging in innovative activities. From the Spanish Innovation Survey 2007, factors associated with availability of finance are deemed as the most important barriers for firms (about 30% of firms reporting that these barriers have been very important), followed by market related barriers (about 20%) and knowledge related barriers (about 10%).

Most studies focus on the determinants of innovation (Freeeman, 1990; Cohen, 1995; Kleinknecht and Mohnen, 2001). Researchers and theorists agree that the organizations can have specific features like structure, culture, and processes that stimulate innovation (Amabile, 1988; Hamel, 2000). Obstacles to the innovation are of opposite nature and are discussed less in comparison to determinants. Still several empirical studies of innovation obstacles have been executed in Europe: Ylinenpää (1998) in Sweden, Mohnen and Rollers (2003) have made research for Ireland, Denmark, Germany and Italy. Galia and Legros (2004), Savignac (2006) researched obstacles for French firms.

Using Community Innovation Survey data for European countries, Canepa and Stoneman (2002) found that financial constraints have more of an impact on not starting, delaying or postponing projects than other internal or external hampering factors. Other obstacles to innovations have received some attention too in the theoretical and empirical literature. Tiwari et al. (2007) found that older firms and firms that belong to a group are less likely to be financially constrained.

Government, its policies and regulations, is a frequent source of barriers to innovation (Pol et al., 1999). He views barriers as a component of a national innovation climate in the country. Bureaucratic procedures, lack of properly settled national strategy, problems in policy communication and execution may cause abnormal external barriers for innovation process. Piater (1984) admits that lack of government assistance was the third most important barrier to innovation in European countries.

Mohnen and Röller (2005) consider the obstacles to innovation as indications of failures or weaknesses in the corresponding innovation policies. They argue whether innovation policies are enforcers or substitutes in the sense of reinforcing their negative effect on innovation behaviour and innovation result. The research evidence suggests that substitutability among policies is more often the norm as far as the intensity of innovation is concerned. Governments should adopt a different types and elements of policies, for instance aide access to finance, promotion of Triple helix; allow firms to cooperate with other firms and technological institutions, or increase the amount of skilled personnel and reduce the regulatory issues. Klein (2002) has classified five barriers existing on ‘’ individual’’ or ‘’organizational’’ level: ability barriers; knowledge barriers; functional barriers; intentional barriers and affective barriers. Internal barriers have to be perceived to be more important than the external ones. They are easier to identify and deal with.

Klein's (2002) classification of innovation barriers is similar to Corsten's (1989), which defines that innovation barrier can be individual or organization related.

Two most important groups among ‘’person’’ or ’’ individual’’ barriers are: ability and motivation. Abilities can be restricted by person's knowledge and functional level. The knowledge barriers arise due to lacking knowledge or low absorptive capacity. Organizational barriers may arise from ineffective structure or culture. Financial barriers are among the most often mentioned to innovation fostering. The risk of costs, viability assessment and financing of innovation according to Freel (2000) are the main obstacles. Hall (2000) also admits that financial problems are particularly acute in the case of innovation activities due to some of their inherent characteristics. Innovation projects are riskier than physical investment projects and therefore outside investors require a high risk taking approach for the financing of innovation activities. Savignac (2006) reports that 17.25 % businesses with more than 500 employees and a sample of small business firms suffer from financing constraints.

Another area of innovation obstacles is related to a weak management commitment, which does not support innovation culture. Most issues related to unsupportive innovation culture are directly related to manager management style (Mosey et al. 2002).

CHAPTER 3: METHODOLOGY

3.1 Data Source

The data used in this survey is from Ghana National System of Innovation Survey that was carried out by the United Nations Industrial Development Organization (UNIDO), and looked at Ghana's National System of Innovation. The study that was concluded in late 2012, was conducted in conjunction with Ghana's Ministry of Trade and Industry and key national stakeholders, the Kwame Nkrumah University of Science and Technology (KNUST), and the Science and Technology Policy Research Institute (STEPRI).

The sample population was composed of senior persons within the hierarchy of Government, KBIs, Medium- and High-Tech Industry (MHTI) and Arbitrageurs, and the rate of response from such a group is expected, at best, about 32%. For the GNSI survey a universe of 558 respondents was identified. From this, due to changes in contact information and inability to access current information and inactive email addresses, a convenient sample of 444 was obtained. The convenient sample was surveyed for a period of 6 months the end result being a total number of 234 responses (52.7%).

Actor	Universe	Convenient Sample	Responses	Response Rate (%)
Government	260	166	39	33.6
MHT Industry	120	87	60	68.9
Knowledge-Based Institutions	182	175	129	73.3
Arbitrageurs (Financial Institutions, Venture Capitalists/Knowledge Brokers)	16	16	6	37.5
All Actors	578	444	234	52.7

*Note: the convenient sample represents Respondents whose contact details were verified through the UNIDO verification protocol.

Data was collected using the FOSS application Lime Survey. The online questionnaire consisted of 138 variables. Some of the variables include level of innovativeness; barriers to innovation and policy instrument success; underlying factors to barriers to innovation; policy instruments and success; and underlying factors to policy success.

For this study data on *"Which of the following variables constrain innovation in your country?"* question/variable is used do carry out the analysis. The question/variable had following variables;

Which of the following variables constrain innovation in your country?	
d101	Lack of explicit policy support
d102	Lack of finance
d103	Lack of technically trained manpower
d104	Quality of technically trained manpower
d105	Hierarchical organizations
d106	Brain Drain
d107	Lack of competition
d108	Lack of demanding customers
d109	Lack of innovative customers
d110	Lack of higher resolution regulations
d111	Lack of information (knowledge gap)
d112	Organizational rigidities
d113	Innovation costs (too high)
d114	Excessive perceived economic risk
d115	Restrictive public / governmental regulations
d116	Rate of access to ICT
d117	ICT capacity

3.2 Factor Analysis.

Factor analysis is a method for investigating whether a number of variables $Y_1, Y_2, ..., \mathrm{Y}_\mathrm{m}$ of interest are linearly related to a smaller number of unobservable factors $F_1, \mathrm{F}_2, ..., \mathrm{F}_K$.

The starting point of factor analysis is a correlation matrix, in which the intercorrelations between the studied variables are presented. The dimensionality of this matrix can be reduced by "looking for variables that correlate highly with a group of other variables, but correlate very badly with variables outside of that group" (Field 2000: 424). These variables with high intercorrelations could well measure one underlying variable, which is called a 'factor'.

Factor analysis has the following two assumptions;

- The variables should be quantitative at the interval or ratio level. Data for which Pearson correlation coefficients can sensibly be calculated should be suitable for factor analysis.
- The data should have a bivariate normal distribution for each pair of variables, and observations should be independent.

3.2.1 Testing normality

There are several methods of assessing whether data are normally distributed or not. They fall into two broad categories: graphical and statistical. The some common techniques are:

<u>Graphical</u>

- Q-Q probability plots
- Cumulative frequency (P-P) plots

<u>Statistical</u>

- W/S test
- Jarque-Bera test
- Shapiro-Wilks test
- Kolmogorov-Smirnov test
- D'Agostino test

Statistical tests for normality are more precise since actual probabilities are calculated.
Tests for normality calculate the probability that the sample was drawn from a normal population.
We will use Shapiro-Wilk (SW) test to demonstrate how statistical test for normality can be done.
The basic approach used in the Shapiro-Wilk (SW) test for normality is as follows:

- Rearrange the data in ascending order so that $x_1 \leq ... \leq x_n$.
- Calculate SS as follows:

$$ss = \sum_{i=1}^{n} (x_i - \overline{x})^2$$

- If n is even, let $m = n/2$, while if n is odd let $m = (n–1)/2$
- Calculate b as follows, taking the a_i weights from Appendix 10 (based on the value of n) in the Shapiro-Wilk Table. Note that if n is odd, the median data value is not used in the calculation of b.

$$b = \sum_{i=1}^{m} \mathrm{a_i} (x_{n+1-i} - x_i)$$

- Calculate the test statistic $W = b2 / SS$
- Find the value in Appendix 11 of the Shapiro-Wilk Table (for a given value of n) that is closest to W, interpolating if necessary. This is the probability that the data comes from a normal distribution.

For example, suppose $W = .975$ and $n = 10$. This means that the probability that the data comes from a normal distribution is somewhere between 90% and 95%. SW is valid for samples from about n = 7 to 2000.

3.2.2 Correlation matrix.

Covariance measures the relationship between two variables. It is given by;

$$Cov(X_i X_j) = E(X_i - \mu_i)(X_j - \mu_j)'$$

The correlation matrix comes from the variance-covariance matrix. Recall that the sample variance is; $S^2 = \frac{\sum_{i\in S}(x_i - \bar{x})^2}{n-1}$ the numerator of which can be written as: $\sum_{i\in S}(x_i - \bar{x})\ (x_i - \bar{x})$. It is a sum of squares. This idea of sum of squares can be generalized, for example, to $SS_{xy} = \sum_{i\in S}(x_i - \bar{x})(\mathrm{y}_i - \bar{y})$. we see that with the generalized notation $SS_{xx} = \sum_{i\in S}(x_i - \bar{x})(x_i - \bar{x})$. If there is a third variate like then $SS_{yz} = \sum_{i\in S}(\mathrm{y}_i - \bar{y})(\mathrm{z}_i - \bar{z})$, and so on. These sums of squares are consolidated into a compact form by using the notation of matrices as in:

$$\Sigma = \frac{1}{n-1}\begin{bmatrix} S_{xx} & S_{xy} & S_{xz} \\ S_{yx} & S_{yy} & S_{yz} \\ S_{zx} & S_{zy} & S_{zz} \end{bmatrix} \qquad [1.1]$$

Which gives us the variance covariance matrix shown below;

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2p} \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ \sigma_{p1} & \sigma_{p2} & \cdots & \sigma_{pp} \end{bmatrix} \quad \text{*Note} \quad \sigma_{ii} = \sigma_i^2 \qquad [1.2]$$

Σ has p and $p(p-1)/2$ covariance (symmetric).

The matrix Σ is estimated by matrix S given by;

$$S = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \underline{\bar{X}}_i)(X_i - \underline{\bar{X}}_i)'$$

Where $\underline{X}_i{}' = [X_{i1}, X_{i2}, ..., X_{ip}]$, S - sample covariance matrix.

The correlation between two variables X and Y is defined from the covariance as follows;

$$\rho_{XY} = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X)\,\text{Var}(Y)}} = \frac{\sigma_{XY}}{\sqrt{\sigma_{XX}\sigma_{YY}}}$$

The advantage of the correlation is that it is independent of the scale, i.e., changing the variables' scale of measurement does not change the value of the correlation. Therefore, the correlation is more useful as a measure of association between two random variables than the covariance. The empirical version of ρ_{XY} is as;

$$r_{XY} = \frac{s_{XY}}{\sqrt{s_{XX}s_{YY}}}$$

The correlation is in absolute value always less than 1. It is zero if the covariance is zero and vice-versa. For p-dimensional vectors $(X_1, X_2 ..., X_p)^T$ we have the theoretical correlation matrix;

$$\rho = \begin{bmatrix} \rho_{X_1X_1} & \rho_{X_1X_2} & \cdots & \rho_{X_1X_p} \\ \rho_{X_2X_1} & \rho_{X_2X_2} & \cdots\cdot & \rho_{X_2X_p} \\ . & & & \\ . & & & \\ . & & & \\ \rho_{X_pX_1} & \rho_{X_pX_2} & \cdots & \rho_{X_pX_p} \end{bmatrix} = \begin{bmatrix} 1 & \rho_{12} & \cdots & \rho_{1p} \\ \rho_{21} & 1 & \cdots & \rho_{2p} \\ . & & & . \\ . & & & . \\ . & & & . \\ \rho_{p1} & \rho_{p2} & \cdots & 1 \end{bmatrix}, \qquad [1.3]$$

$$\rho = \begin{bmatrix} \rho_{xx} & \rho_{xy} & \rho_{xz} \\ \rho_{yx} & \rho_{yy} & \rho_{yz} \\ \rho_{zx} & \rho_{zy} & \rho_{zz} \end{bmatrix}$$

and its empirical version, the empirical correlation matrix which can be calculated from the observations is;

$$R = \begin{bmatrix} r_{X_1X_1} & r_{X_1X_2} & \cdots & r_{X_1X_p} \\ r_{X_2X_1} & r_{X_2X_2} & \cdots & r_{X_2X_p} \\ . & & & \\ . & & & \\ . & & & \\ r_{X_pX_1} & r_{X_pX_2} & \cdots & r_{X_pX_p} \end{bmatrix} \qquad [1.4]$$

3.2.3 Factorability of the correlation matrix

A correlation matrix should be used in the EFA process displaying the relationships between individual variables. Henson and Roberts pointed out that a correlation matrix is most popular among investigators. Tabachnick and Fidell recommended inspecting the correlation matrix (often termed Factorability of R) for correlation coefficients over 0.30.

Hair et al. (1995) categorized these loadings using another rule of thumb as ±0.30=minimal, ±0.40=important, and ±.50=practically significant. If no correlations go beyond 0.30, then the researcher should reconsider whether factor analysis is the appropriate statistical method to utilize.

Another method of checking the suitability of factor analysis is to check the determinant of the correlation matrix. The determinant should be greater than 0.00001, showing that there is no multicollinearity problem. If multicollinearity is there one should consider removing some of the variables.

Suppose we have a square matrix $A = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$,then its determinant which is denoted by $|A|$ will be given by;

$$|A| = a \cdot \begin{vmatrix} e & f \\ h & i \end{vmatrix} - b \cdot \begin{vmatrix} d & f \\ g & i \end{vmatrix} + c \cdot \begin{vmatrix} d & e \\ g & h \end{vmatrix} \qquad [1.5]$$

3.2.4 Sample Adequacy and Sphericity

Prior to the extraction of the factors, several tests should be used to assess the suitability of the respondent data for factor analysis. These tests include Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, and Bartlett's Test of Sphericity. The KMO index, in particular, is recommended when the cases to variable ratio are less than 1:5. The KMO index ranges from 0 to 1, with 0.50 considered suitable for factor analysis.

Let $S^2 = diag(\mathrm{R}^{-1})^{-1}$ and $Q = SR^{-1}S$. Then Q is said to be the anti-image intercorrelation matrix. Let $sumr^2 = \sum R^2$ and $sumq^2 = \sum Q^2$ for all off diagonal elements of R and Q,then $MSA = (sumr^2) / \left(sumr^2 + sumq^2\right)$ Although originally MSA was $1 - sumq2/sumr2$ (Kaiser, 1970), this was modified in Kaiser and Rice, (1974) to be $MSA = (sumr^2) / \left(sumr^2 + sumq^2\right)$ This is the formula used by Dziuban and Shirkey (1974) and by SPSS.

The Bartlett's test checks if the observed correlation matrix $R = (r_{ij})_{(p \times p)}$ diverges significantly from the identity matrix (theoretical matrix under H0: the variables are orthogonal). The PCA can perform a compression of the available information only if we reject the null hypothesis.

In order to measure the overall relation between the variables, we compute the determinant of the correlation matrix |R|. Under H0, |R| = 1; if the variables are highly correlated, we have $|R| \approx 0$.

The Bartlett's test statistic indicates to what extent we deviate from the reference situation |R| = 1.

It uses the following formula.

$\chi^2 = -\left(n - 1 - \frac{2p+5}{6}\right) \times \ln|R|$ where n-instance and p-variables.

Under H0, it follows a χ^2 distribution with a [p x (p-1) / 2] degree of freedom.

The Bartlett's Test of Sphericity should be significant (p-value<.05) for factor analysis to be suitable.

A p-value is something you calculate when you want to evaluate two competing hypotheses. Given a pair of competing hypotheses (H_0 *and* H_A), a p-value is calculated from relevant data you have gathered. The p-value you get from your data will give you an idea of how plausible the hypotheses you are evaluating are.

Suppose we have a game in which people bet on whether a coin will come up heads or tails when it is tossed. This game is perfectly legal as long as the coin is fair, meaning that every time it is tossed there is a 50 percent chance it comes up heads and a 50 percent chance it comes up tails. An agent from the Betting and Control Board suspects that the game has been using a weighted coin that has a greater probability of coming up heads than of coming up tails. The owner of the game is arrested and is on trial.

We can have the null hypothesis, that the game owner is innocent, and the alternative, that he is guilty, can be written like this:

$$H_0 : p = 0.5$$
$$H_A : p > 0.5$$

Where *p* represents the probability that the coin comes up heads on any toss.

Suppose ten tosses are made and the outcome is HHHHTHHHTH. To get the p-value, we define a "test statistic," a value that we calculate from our raw data that will be useful in evaluating the competing hypotheses. The choice of a test statistic is an intuitively plausible. So let us take the number of heads observed in ten tosses as the test statistic.

Next, we ask: "Qualitatively speaking, what values of the test statistic would challenge the null and support the alternative?" In this example, it is *large* values of the test statistic that look inconsistent with the null.

If we let *X* represent the number of heads in ten tosses of the coin, we can write;

$$p - value = P(X \geq 8 \mid the\ \ null\ \ hypothesis\ \ is\ \ true)$$

To calculate this probability, we somehow need to figure out the probability distribution of the test statistic *X*. In this case, it is easy: assuming the tosses of the coin are mutually independent (which is reasonable in this case), the number of heads in ten tosses is a binomial random variable. But what are the parameters of this binomial random variable? The number of trials is ten, but do we know the probability of getting heads on any given trial? If we did, we wouldn't have to do this hypothesis test! So all we can say is that the probability of heads on any trial is *p*, where *p* is the true, but unknown, probability of getting heads on any toss. So what we know for sure about the distribution of *X* can be written as $X \sim Bin(10, p)$.

But the p-value is not simply the probability that X is greater than or equal to eight. The question is, what would that probability be if the null hypothesis were true? And since the null hypothesis is that $p = .5$, we can say the following: If the null hypothesis is true, then $X \sim Bin(10,.5)$. [You sometimes hear terminology like "*under the null hypothesis*, $X \sim Bin(10,.5)$," or "the *null distribution* of X is binomial with n=10 and p=.5."]

So now we can say more about the p-value. In fact we can calculate it:

$$\begin{aligned} p-value &= P(X \geq 8 \mid \textit{the null hypothesis is true}), \textit{ where } X \sim Bin(10,p) \\ &= P(X \geq 8), \textit{ assuming } X \sim Bin(10,.5) \\ &= .0547 \end{aligned}$$

This means that there is just a 5.47 percent chance of getting eight or more heads in ten tosses of a fair coin. More pointedly, if the coin in question in this trial were fair, there would be just a 5.47 percent chance of getting as many heads as we did when we tossed it ten times.

3.2.5 Mathematics of the factor analysis model.

We assume that we have a set of observed or manifest variable $\underline{X'} = (X_1, X_2, ...Xq)$,assumed to be linked to a smaller number of unobserved latent variable $f_1, f_2, ...f_k$,where k<q ,by a regression model of the form;

$$\begin{aligned} X_1 &= \lambda_{11} f_1 + \lambda_{12} f_2 + ... + \lambda_{1k} f_k + \mu_1 \\ X_2 &= \lambda_{21} f_1 + \lambda_{22} f_2 + ... + \lambda_{2k} f_k + \mu_2 \\ &. \\ &. \\ &. \\ X_q &= \lambda_{q1} f_1 + \lambda_{q2} f_2 + ... + \lambda_{qk} f_k + \mu_q \end{aligned} \qquad [1.6]$$

The λ_{ij}'s are weights showing each X_i depends on the common factors.

The λ_{ij}'s are used in the interpretation of the factors i.e. larger values relate a factor to the corresponding observed variable and from this we infer a meaningful description of each factor.

Equation [1.6] may be written more concisely in matrix form as;

$$\underline{X} = \lambda \underline{f} + \underline{\mu} \qquad [1.7]$$

Where $\lambda = \begin{bmatrix} \lambda_{11}...\lambda_{1k} \\ \lambda_{21}...\lambda_{2k} \\ . \\ . \\ . \\ \lambda_{q1}...\lambda_{qk} \end{bmatrix}$ represent the *factor loadings*.

$\underline{f} = \begin{pmatrix} f_1 \\ . \\ . \\ . \\ f_k \end{pmatrix}$ represent the *factors.*

$\underline{\mu} = \begin{pmatrix} \mu_1 \\ . \\ . \\ . \\ \mu_q \end{pmatrix}$ represent the *specific variate.*

In equation [1.7], the following assumptions are made;

- The "residuals" term $\mu_1, \mu_2 ..., \mu_q$ are uncorrelated with each other and with the factors $f_1, f_2 ..., f_k$.
- The elements of μ are specific to each x_i and hence are known as specific variates.

The two assumptions above imply that given the value of the factors, the manifest variable are independent i.e. the correlations of the observed variable arise from their relationship with the factors. In factor analysis, the regression coefficients in λ are more usually known as factor loadings.

Since factor analysis usually works with the variances and covariances of the observed x variables, it is sometimes referred to as ''the analysis of covariance structures''. Some hint of this is apparent in equation (1.6), where the absence of an intercept term suggests that the means of the observed variables are either zero or of no direct interest. Indeed, this is typically the case in factor analysis, where the task is to learn about inter-relationships among variables rather than model the levels of each variable. Moreover, it is generally not possible to estimate both the factor loadings and intercept terms (cf Jöreskog and Sörbom, 1989, ch10). Consequently, all the x variables and the unobserved f are presumed to have zero means, constraining any intercept term in equation (1.6) to zero.

Variance of variable x_i ;

$$\delta_i^2 = \sum_{j=1}^{k} \lambda_{ij}^{\ 2} + \psi_i$$

Where ψ_i is the variance of μ_i i.e. variance of x_i can be split.

$h_i^2 = \sum_{l=1}^{k} \lambda_{ij}^{\ 2}$ is known as the communality. Which is the variance shared with other variable via the common factors.

ψ_i is the specific or unique variance. It is the variability of x_i not shared with other variables.

$$\operatorname{cov}(X_i X_j) = \delta_{ij} = \sum_{l=1}^{k} \lambda_{il} \lambda_{jl}$$

δ_{ij} do not depend on the specific variates in any way, the common factors above accounts for the relationship between the manifest variables i.e.

$$\sum = \Lambda\Lambda' + \psi \quad \text{Where, } \psi = diag(\psi_i) \qquad [1.8]$$

3.2.6 How to decompose

To decompose $\sum$ or estimate S or R into the form $\Lambda\Lambda' + \psi$ we will also need to determine the value of K (the number of factors), so that the model provide an adequate fit to S or R .

The estimation problem of factor analysis is essentially that of finding $\hat{\Lambda}$ and $\hat{\psi}$ which;

$$S = \hat{\Lambda}\hat{\Lambda}' + \psi \text{ or } R = \hat{\Lambda}\hat{\Lambda}' + \psi \qquad [1.9]$$

3.2.7 Factor Analysis Extraction Methods

There are numerous ways to extract factors: Principal components analysis (PCA), principal axis factoring (PAF), image factoring, maximum likelihood, alpha factoring, and canonical. The most common extraction methods are listed below;

- Principal components analysis (PCA)
- Principal axis factoring (PAF)
- Maximum likelihood
- Unweighted least squares
- Generalised least squares
- Alpha factoring
- Image factoring

However, PCA and PAF are used most commonly in the published literature. The decision whether to use PCA and PAF is fiercely debated among analysts, although according to Thompson the practical differences between the two are often insignificant, particularly when variables have high reliability, or where there are 30 or more variables.

Thompson noted that PCA is the default method in many statistical programs, and thus, is most commonly used in EFA. However, PCA is also recommended when no priori theory or model exists. Pett et al. (2003) suggested using PCA in establishing preliminary solutions in EFA.

3.2.8 Factor Analysis and Inference for Structured Covariance Matrix.

The observable random variable $\underline{X}$ with P components has mean μ and covariance matrix $\sum$.The factor model postulates that X is linearly dependent upon a few unobservable random variable $f_1, f_2, ..., f_m$ called common factors, and P additional source of variation $\varepsilon_1, \varepsilon_2, ..., \varepsilon_p$ called error or specific factors.

$$X_1-\mu_1=l_{11}f_1+l_{12}f_2+...+l_{1m}f_m+\varepsilon_1$$
$$X_2-\mu_2=l_{21}f_1+l_{22}f_2+...+l_{2m}f_m+\varepsilon_2$$
.

.

.

$$X_p-\mu_p=l_{p1}f_1+l_{p2}f_2+...+l_{pm}f_m+\varepsilon_p$$

In matrix notations;

$\underline{X}-\underline{\mu}=L\underline{F}+\underline{\varepsilon}$

Since $\mu=0$ it can be deleted to get;

$$\underline{\mathrm{X}}=L_{(p\times m)}\underline{F}_{(m\times 1)}+\underline{\varepsilon}_{(p\times 1)} \qquad [1.10]$$

l_{ij} -loadings of the i variable on j factor.

$f_1, f_2,...., f_m, \varepsilon_1, \varepsilon_2, ..., \varepsilon_p$ are unobservable.

$\underline{F}$ and $\underline{\varepsilon}$ are random vectors satisfying the following conditions (factor analysis model assumptions);

- The unobservable factors F_j are independent of one another and of the error terms,

$$E[\underline{F}]=0 \quad Cov(\underline{F})=E[\underline{F}\underline{F}']=\mathrm{I}_{m\times m}$$

- The error terms ε_i are independent of one another,

$$E[\underline{\varepsilon}]=0 \quad Cov(\underline{\varepsilon})=E[\underline{\varepsilon}\underline{\varepsilon}']=\psi_{p\times p}=\begin{bmatrix}\psi_1 & 0 & ... & 0\\ 0 & \psi_2 & ... & 0\\ . & & & \\ . & & & \\ . & & & \\ 0 & 0 & ... & \psi_p\end{bmatrix}$$

$Cov(\underline{\varepsilon},\underline{F}) = \mathrm{E}(\underline{\varepsilon}\underline{F}') = \underset{(p\times m)}{0}$ i.e. $\underline{F}$ and $\underline{\varepsilon}$ are independent.

A factor model with M common factors will have the following form;

$\underline{X} = \underline{\mu} + L\underline{F} + \underline{\varepsilon}$, where [1.11]

μ_i - mean of variable i

ε_i - i^th specific factor

f_j - j^th common factor

l_{ij} - loading of the i^th variable on the j^th factor

The unobservable random vectors $\underline{F}$ and $\underline{\varepsilon}$ satisfy the conditions mentioned above.

3.2.9 Covariance structure

$$\sum = Cov(X) = E(\underline{X}-\underline{\mu})(\underline{X}-\underline{\mu})'$$

$$= E(L\underline{F}+\underline{\varepsilon})(L\underline{F}+\underline{\varepsilon})'$$

$$= E[L\underline{F}+\underline{\varepsilon}((L\underline{F})'+\underline{\varepsilon}')]$$

$$= \mathrm{E}[(LF(LF)'+\underline{\varepsilon}(L\underline{F})'+LF\underline{\varepsilon}'+\underline{\varepsilon\varepsilon}']$$

$$= LE\underline{F}\underline{F}'L' + E(\underline{\varepsilon}\underline{F})'L + LE(\underline{F}\underline{\varepsilon}') + E(\underline{\varepsilon\varepsilon}')$$

$$= LL' + \psi \qquad [1.12]$$

Also;

$$Cov(\underline{X},\underline{F}) = E(\underline{X}-\underline{\mu})\underline{F}' = E(L\underline{F}+\underline{\varepsilon})\underline{F}' = E(L\underline{F}\underline{F}'+\underline{\varepsilon}\underline{F}')$$

$$= LE(\underline{F}\underline{F}') + E(\underline{\varepsilon}\underline{F}')$$

$$= L$$

3.2.10 Covariance structure of a factor model (orthogonal)

i. $Cov(X) = LL' + \psi$ or

$$Var(X_i) = l_{i1}^{\;2} + l_{i2}^{\;2} + ... + l_{im}^{\;2} + \psi_i$$
$$Cov(X_i X_k) = l_{i1} l_{k1} + ... + l_{im} l_{km}$$

ii. $Cov(X, F) = L$

$Cov(X_i, F_j) = L_{ij}$

The proportion of variance of the i^th variable contributed by the m common factors is called the i^th communality. The proportion of $Var(X_i) = \sigma_{ii}$ due to the specific factor is often called Uniqueness (specific Variance).

$\sigma_{ii} = h_i^2 + \psi_{ii} \qquad i = 1, 2, ... \text{p}$

$$\sigma_{ii} = \underbrace{l_{i1}^{\;2} + l_{i2}^{\;2} + ... + l_{im}^{\;2}}_{Communality} + \underbrace{\psi_i}_{Specific\ Variance} \qquad [1.13]$$

$Var(X_i) = Communality + Specific\ Variance$

3.2.11 Non-Uniqueness of Factor Loadings

Factor loadings L are determined only up to an orthogonal matrix T. Thus the loadings $L^* = LT \ and \ L$ both give the same representation. The communalities given by the diagonal elements of $LL' = (L^*)(L^*)$ are also affected by the choice of T.

Explanation: Let T be an m x m orthogonal matrix, so that;

$\text{TT}' = \text{T}'\text{T} = \text{I}$

$X - \mu = LF + \underline{\varepsilon} = LTT'F + \underline{\varepsilon} = L^* F^* + \underline{\varepsilon}$

Where;

$$L^* = LT \ and \ F^* = T'F$$

$$E[F^*] = T'E(F) = 0$$

$$Cov[F^*] = T'Cov[F]T = \mathrm{TT}' = \mathrm{I}_{m\times m}$$

Thus $\sum = LL' + \psi = LTT'L' + \psi = (L^*)(L^*)' + \psi$

3.2.12 Principal Component Analysis.

Principal component solution of the Factor Model.

Consider the data below which represent a sample from data collected on variables affecting innovation. X_1, X_2 and X_3 represent the variables affecting innovation. Each question was responded to using a 5 point Likert scale with possible responses:

1. Very Strong; 2. Strong; 3. Medium; 4. Weak; 5. Very Weak.

Table 1:

Institution	**Lack of explicit policy(X_1)**	**Lack of finance(X_2)**	**Lack of technically trained manpower(X_3)**
1	3	2	1
2	1	2	2
3	2	1	1
4	1	2	3
5	2	4	2

The principal component factor analysis of the sample covariance matrix S is specified in terms of its eigenvalue-eigenvector pair $(\lambda_1 \underline{e}_1), (\lambda_2 \underline{e}_2), \ldots, (\lambda_p \underline{e}_p)$ where $\lambda_1 \geq \lambda_2 \geq \lambda_3$.

From the data in table 1.

$$\sum = \begin{bmatrix} 0.7 & 0.05 & -0.55 \\ 0.05 & 1.2 & 0.3 \\ -0.55 & 0.3 & 0.7 \end{bmatrix}$$

[1.14]

3.2.13 Eigenvalues and Eigenvectors

For every square matrix A, a scalar λ and a nonzero vector $\underline{x}$ can be found such that;

$$A\underline{x} = \lambda \underline{x}$$

$$A\underline{x} - \lambda \underline{x} = \underline{0}$$

$$(A - \lambda \mathrm{I})\underline{x} = \underline{0}$$

The eigenvalues and eigenvectors for equation [1.14] can be gotten as follows;

$$(\Sigma - \lambda \mathrm{I})\underline{x} = \underline{0} \Rightarrow \begin{vmatrix} 0.7-\lambda & 0.05 & -0.55 \\ 0.05 & 1.2-\lambda & 0.3 \\ -0.55 & 0.3 & 0.7-\lambda \end{vmatrix} \qquad [1.15]$$

$$= 0.7-\lambda \begin{vmatrix} 1.2-\lambda & 0.3 \\ 0.3 & 0.7-\lambda \end{vmatrix} - 0.05 \begin{vmatrix} 0.05 & 0.3 \\ -0.55 & 0.7-\lambda \end{vmatrix} - 0.55 \begin{vmatrix} 0.05 & 1.2-\lambda \\ -0.55 & 0.3 \end{vmatrix}$$

$$= 0.7-\lambda\left[((1.2-\lambda)*(0.7-\lambda))-(0.3*0.3)\right]-0.05\left[(0.05*0.7-\lambda)-(-0.55*0.3)\right]-0.55\left[(0.05*0.3)-(-0.55*(1.2-\lambda))\right]$$

Solving this will give the following eigenvalues;

$$\lambda_1 = 1.42578434;\ \lambda_2 = 1.08094374;\ \lambda_3 = 0.09327192 \qquad [1.16]$$

Replacing the values of λ_1, λ_2 *and* λ_3 in [1.16] in equation [1.15] and solving for x_i's and getting the orthogonal gives us the eigenvectors.

Example let's take $\lambda_1 = 1.42578434 \approx 1.43$ then;

$$\begin{pmatrix} 0.7-1.43 & 0.05 & -0.55 \\ 0.05 & 1.2-1.43 & 0.3 \\ -0.55 & 0.3 & 0.7-1.43 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} -0.73 & 0.05 & -0.55 \\ 0.05 & -0.23 & 0.3 \\ -0.55 & 0.3 & -0.73 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \Rightarrow \begin{matrix} -0.73x_1 + 0.05x_2 - 0.55x_3 = 0 \\ -0.05x_1 - 0.23x_2 + 0.3x_3 = 0 \\ -0.55x_1 + 0.32x_2 - 0.73x_3 = 0 \end{matrix} \qquad [1.17]$$

Solving [1.17] simultaneously and getting the orthogonal gives us the following eigenvectors;

$$\underline{x}_1 = \begin{bmatrix} -0.41 \\ 0.70 \\ 0.59 \end{bmatrix}$$

Similarly replacing λ_2 *and* λ_3 and solving the equations gives us;

$$\underline{x}_2 = \begin{bmatrix} 0.63 \\ 0.68 \\ -0.38 \end{bmatrix} \qquad \underline{x}_3 = \begin{bmatrix} 0.67 \\ -0.22 \\ 0.71 \end{bmatrix}$$

3.2.14 Factor loadings

Let $m < p$ be the number of common factors. Then the matrix of estimated factor loadings $\hat{L}_{ij}$ is given by;

$$\hat{\mathrm{L}} = \left[\sqrt{\hat{\lambda}_1}\,\underline{\hat{e}}_1 \vdots \sqrt{\hat{\lambda}_2}\,\underline{\hat{e}}_2 \vdots \ldots \vdots \sqrt{\hat{\lambda}_m}\,\underline{\hat{e}}_m \right] \qquad [1.18]$$

For the data in table 1, the matrix will be;

$$\hat{\mathrm{L}} = \left[\sqrt{\hat{\lambda}_1}\,\underline{\hat{e}}_1 \vdots \sqrt{\hat{\lambda}_2}\,\underline{\hat{e}}_2 \vdots \sqrt{\hat{\lambda}_3}\,\underline{\hat{e}}_3 \right] \quad where; \begin{matrix} \underline{e}_1 = \underline{x}_1 \\ \underline{e}_2 = \underline{x}_2 \\ \underline{e}_3 = \underline{x}_3 \end{matrix}$$

$$\hat{\mathrm{L}} = \left[\sqrt{1.43}\begin{bmatrix} -0.41 \\ 0.70 \\ 0.59 \end{bmatrix} \vdots \sqrt{1.08}\begin{bmatrix} 0.63 \\ 0.68 \\ -0.38 \end{bmatrix} \vdots \sqrt{0.09}\begin{bmatrix} 0.67 \\ -0.22 \\ 0.71 \end{bmatrix} \right]$$

$$\hat{\mathrm{L}} = \begin{bmatrix} -0.48 & 0.66 & 0.20 \\ 0.83 & 0.71 & -0.07 \\ 0.71 & -0.39 & 0.22 \end{bmatrix}$$

But in factor analysis there is a rule that only factors or components with eigenvalue greater than 1 ($\lambda_i \succ 1$) are retained. From [1.16] only λ_1 *and* λ_2 are greater than 1.Hence;

$$\hat{\mathrm{L}} = \begin{bmatrix} -0.48 & 0.66 \\ 0.83 & 0.71 \\ 0.71 & -0.39 \end{bmatrix}$$

$$= \begin{bmatrix} 0.0340 & -0.0202 & 0.0482 \\ -0.0202 & 0.0070 & -0.0124 \\ 0.0482 & -0.0124 & 0.0438 \end{bmatrix} \qquad [1.19]$$

$\psi_1 = 0.0340;\ \psi_2 = 0.0070;\ \psi_2 = 0.0438$

$$\psi = \begin{bmatrix} 0.0340 & 0 & 0 \\ 0 & 0.0070 & 0 \\ 0 & 0 & 0.0438 \end{bmatrix}$$

3.2.15 Communalities

The communalities are estimated as;

$$h_i^2 = l_{i1}^2 + l_{i2}^2 + ... + l_{im}^2 \qquad [1.20]$$

From the data in table1,

$$h_i^2 = l_{i1}^2 + l_{i2}^2$$

Hence;

$$h_1^2 = (-0.48)^2 + 0.66^2$$
$$h_2^2 = 0.83^2 + 0.71^2$$
$$h_3^2 = 0.71^2 + (-0.39)^2$$

The estimated specific variance are provided by the diagonal elements of the matrix $S - \hat{L}\hat{L}'$

$$\psi = \begin{bmatrix} \psi_1 & 0 & \dots & 0 \\ 0 & \psi_2 & \dots & 0 \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ 0 & 0 & \dots & \psi_p \end{bmatrix} \text{with } \psi_i = S_{ii} - \sum_{j=1}^{m} l_{ij}^{\ 2} \Rightarrow \psi_i = S_{ii} - h_i^2 \qquad [1.21]$$

From the data in table 1;

$$S - \hat{L}\hat{L}' = \begin{bmatrix} 0.7 & 0.05 & -0.55 \\ 0.05 & 1.2 & 0.3 \\ -0.55 & 0.3 & 0.7 \end{bmatrix} - \begin{bmatrix} -0.48 & 0.66 \\ 0.83 & 0.71 \\ 0.71 & -0.39 \end{bmatrix} \begin{bmatrix} -0.48 & 0.83 & 0.71 \\ 0.66 & 0.71 & -0.39 \end{bmatrix}$$

$$= \begin{bmatrix} 0.0340 & -0.0202 & 0.0482 \\ -0.0202 & 0.0070 & -0.0124 \\ 0.0482 & -0.0124 & 0.0438 \end{bmatrix}$$

Taking the diagonals gives us;

$\psi_1 = 0.0340$; $\psi_2 = 0.0070$; $\psi_2 = 0.0438$

Hence;

$$\psi = \begin{bmatrix} 0.0340 & 0 & 0 \\ 0 & 0.0070 & 0 \\ 0 & 0 & 0.0438 \end{bmatrix}$$

Table 2. Estimated factor loadings, communalities, and specific variances.

Variable, X_i	**Observed variance** S_i^2	**Estimated factor loadings on**		**Communalities**	**Specific variances**
		$F_1, \hat{l}_1$	$F_2, \hat{l}_2$	h_i^2	$\psi_i = S_{ii} - h_i^2$
Lack of explicit policy(X_1)	0.7	-0.48	0.66	0.666	0.0340
Lack of finance(X_2)	1.2	0.83	0.71	1.193	0.0070
Lack of technically trained manpower(X_3)	0.7	0.71	-0.39	0.6562	0.0438
Overall	2.6	1.4234^a	1.0918^a	2.5152	
^{a} *Sum of squared loadings* $S_{ii} = S_i^2$					

3.2.16 Factor rotation

After factor extraction it might be difficult to interpret and name the factors/components on the basis of their factor loadings. In order to improve interpretability of the factor loadings we can rely on the invariance to orthogonal rotation property of the factor model. In 1947 Thurston gave a definition of how an interpretable (simple) factor structure should be. The variables should be divisible into groups such that the loadings within each group are high on a single factor, perhaps moderate to low on a few factors and negligible on the remaining factors. One way to obtain a factor loading matrix satisfying such a condition is given by the so-called Varimax rotation. It looks for an orthogonal rotation of the factor loading matrix, such that the following criterion is maximized;

$$V = \sum_{k=1}^{m} \left\{ \frac{\sum_{i=1}^{p} \beta_{ik}{}^{4}}{p} - \left(\frac{\sum_{i=1}^{p} \beta_{ik}{}^{2}}{p} \right)^{2} \right\} \quad [1.22]$$

Where

$$\beta_{ik} = \frac{\lambda_{ik}}{\left(\sum_{k=1}^{m} \lambda_{ik}{}^{2} \right)^{1/2}} = \frac{\lambda_{ik}}{h_i}$$

It should be noted that V is the sum of the variances of the squared normalized (within each row) factor scores for each factor. Maximizing it causes the large coefficients to become larger and the small coefficients to approach 0.

A well-known analytical algorithm to rotate the loadings is given by the varimax rotation method proposed by Kaiser (1985). In the simplest case of k = 2 factors, a rotation matrix g is given by;

$$g(\theta) = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \quad [1.23]$$

representing a clockwise rotation of the coordinate axes by the angle θ. The corresponding rotation of loadings is calculated via $\hat{L}^{*} = \hat{L}g(\theta)$. The idea of the varimax method is to find the angle θ that maximizes the sum of the variances of the squared loadings $\hat{l}_{ij}{}^{*}$ within each column of $\hat{L}^{*}$ is maximized.

Other methods for carrying out rotation include;

- Quartimax
- Equamax
- Direct oblimin
- Promax

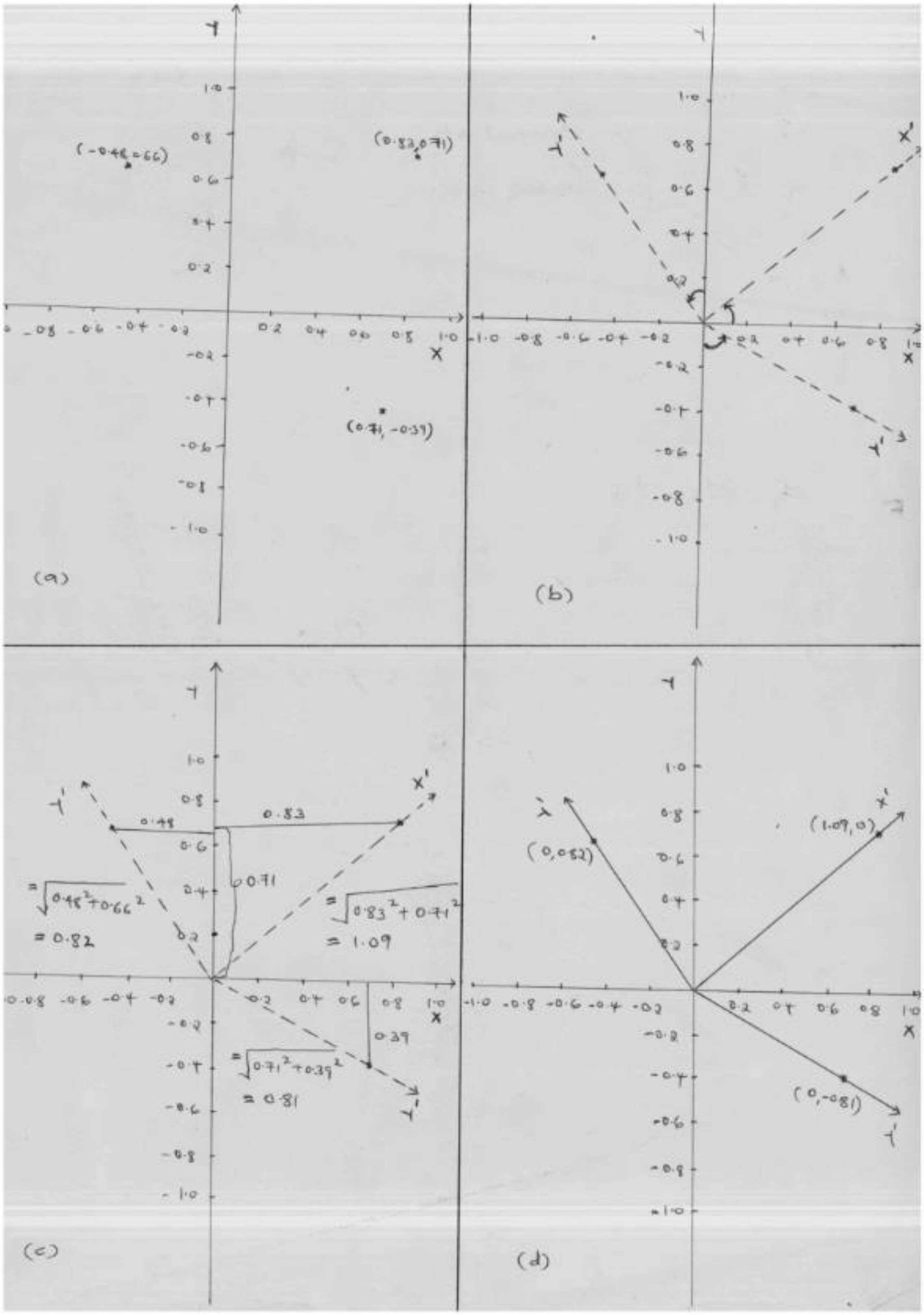
Varimax, quartimax and equamax are orthogonal rotations whereas direct oblimin and promax are oblique rotations. The choice of rotation depends largely on whether or not you think that the underlying factors should be related. If you expect factors to be independent then you should select one of the orthogonal rotations (Varimax is the most recommended).However if there are some theoretical grounds supposing that your factors might correlate then direct oblimin should be selected. We will use orthogonal rotation for our example.

Considering the data in table 1 and the factor loadings in [1.19], we will get the following model;

$$
\begin{aligned}
X_1 &= -0.48F_1 + 0.66F_2 + e_1 \\
X_2 &= 0.83F_1 + 0.71F_2 + e_2 \\
X_3 &= 0.71F_1 - 0.39F_2 + e_3
\end{aligned}
\qquad [1.24]
$$

Plotting the coefficients of F_1 and F_2 for the three equations and rotating the axes as shown in Figure below;

Figure 1: Rotation of loadings illustrated



The above rotation gives us the following new coordinates;

$$\begin{aligned} X_1 &= 0F_1 + 0.82F_2 + e_1 \\ X_2 &= 1.09F_1 + 0F_2 + e_2 \\ X_3 &= 0F_1 - 0.81F_2 + e_3 \end{aligned} \qquad [1.25]$$

Imagine rotating the coordinate axes anticlockwise as shown in Figure 1(b) above to arrive at the new coordinate axes indicated by the dotted lines. The coordinates of the three points with respect to the new axes can be calculated as shown in Figure 1(c).The new coordinates for all three points are shown in Figure 1(d).We see that the loadings of the Model in [1.25] are the result of applying to the loadings of the Model in [1.24] the rotation described above. It can be shown that any other rotation of the original loadings will produce a new set of loadings with the same theoretical variances and covariance's as those of the original model. The number of such rotations is infinite large.
For example the variance and covariance of X_1 in [1.24] is given by;

$$\begin{aligned} Var(X_1) &= (0.83)^2 + (0.71)^2 + \sigma_1^{\,2} = 1.19 + \sigma_1^{\,2} \\ Cov(X_1, X_3) &= (-0.48)(0.71) + (0.66)(-0.39) = -0.5982 \end{aligned} \qquad [1.26]$$

While X_1 in [1.25] is given by;

$$\begin{aligned} Var(X_1) &= (1.09)^2 + (0)^2 + \sigma_1^{\,2} = 1.19 + \sigma_1^{\,2} \\ Cov(X_1, X_3) &= (0)(0) + (0.82)(-0.81) = -0.66 \end{aligned} \qquad [1.27]$$

3.2.17 Factor Scores

The estimated values of the factors, called the factor scores, may also be useful in the interpretation as well as in the diagnostic analysis. To be more precise, the factor scores are estimates of the unobserved random vectors $F_l, l = 1, \ldots, k,$ for each individual $x_i, i = 1, \ldots, n.$ Johnson and Wichern (1998) describe three methods which in practice yield very similar results. Here, we present the regression method which has the advantage of being the simplest technique and is easy to implement.

The idea is to consider the joint distribution of $X-\mu$ and F, and then to proceed with the regression analysis. Under the factor model (1.10), the joint covariance matrix of $X-\mu$ and F is:

$$Var\begin{pmatrix} X-\mu \\ F \end{pmatrix} = \begin{pmatrix} LL'+\psi & L \\ L' & I_k \end{pmatrix} \qquad [1.28]$$

Note that the upper left entry of this matrix equals Σ and that the matrix has size (p +k) $\times$(p + k). Assuming joint normality, the conditional distribution of $F \mid X$ is multinormal with;

$$E(F \mid X = x) = L'\Sigma^{-1}(X-\mu)$$

The covariance matrix can be calculated as;

$$Var(F \mid X = x) = I_k - L'\Sigma^{-1}L.$$

In practice, we replace the unknown L, Σ and μ by corresponding estimators, leading to the estimated individual factor scores:

$$\begin{aligned} &\hat{f}_i = \hat{L}'S^{-1}(x_i - \overline{x}) \\ &\textit{Where;} \\ &\hat{f}_i \Rightarrow \textit{Estimated } i^{th} \textit{ factor score} \qquad [1.29] \\ &\hat{L} \Rightarrow \textit{Matrix of estimated factor loadings} \\ &S \Rightarrow \textit{Variance Covariance matrix} \end{aligned}$$

We prefer to use the original sample covariance matrix S as an estimator of Σ instead of the factor analysis approximation $\hat{L}\hat{L}'+\psi$ in order to be more robust against incorrect determination of the number of factors.

The same rule can be followed when using R instead of S. Then (1.28) remains valid when standardized variables, i.e. $Z = D_{\Sigma}^{-1/2}(X-\mu)$ are considered if $D_{\Sigma} = diag(\sigma_{11},....,\sigma_{pp})$ In this case the factors are given by;

$$\hat{f}_i = \hat{L}'R^{-1}(z_i), \text{ where } z_i = D_S^{-1/2}(x_i - \bar{x}). \qquad [1.30]$$

$\hat{L}$ is the loading obtained with the matrix R, and $D_S = diag(s_{11}, ..., s_{pp})$.

If the factors are rotated by the orthogonal matrix g, the factor scores have to be rotated accordingly, that is;

$$\hat{f}_i^* = g'\hat{f}_i. \qquad [1.31]$$

CHAPTER 4: DATA ANALYSIS AND RESULTS

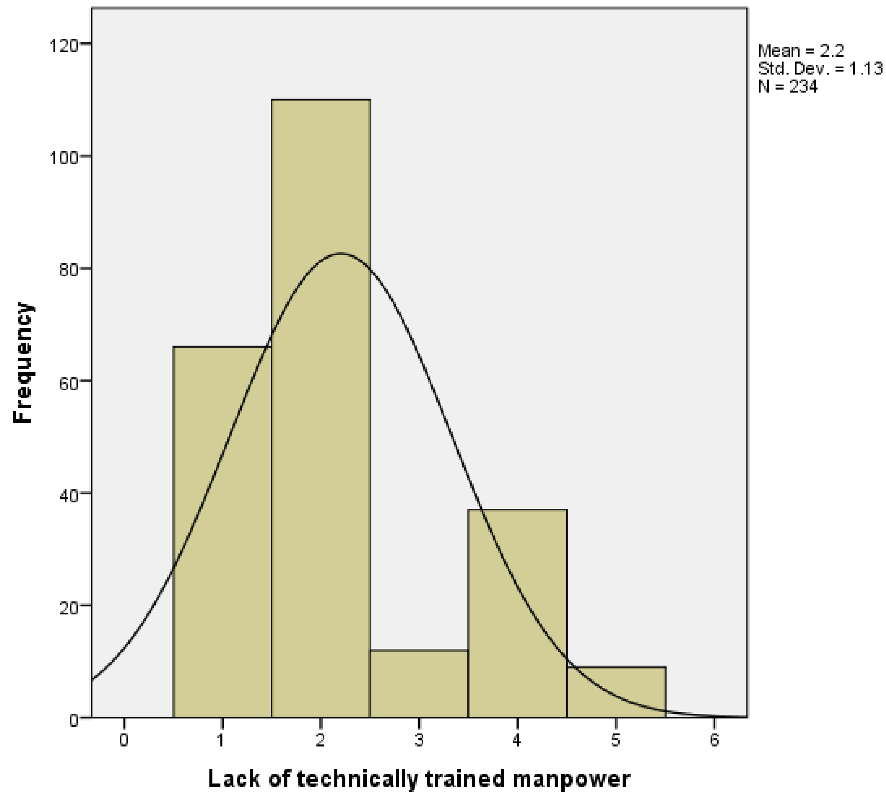
This section will describe how data analysis was conducted and explain the results that were obtained.

4.1 Data Analysis

The data was analyzed using SPSS version 21.

4.1.1 Normality Test

To test normality of variables, a histogram with a normal plot superimposed on it was plotted for each of the variable. And from the plots in can be seen that the data is normally distributed. An example of the plot is shown below.



4.1.2 Correlation Matrix

Appendix 1 shows the R-matrix. It contains the Pearson correlation coefficient between all pairs of questions. We can use this correlation matrix to check the pattern of relationships.

Scan the correlation coefficients and look for any greater than 0.9. If any are found then you should be aware that a problem could arise because of singularity in the data: check the determinant of the correlation matrix and, if necessary, eliminate one of the two variables causing the problem.

For this data its value is greater than the necessary value of 0.00001. Therefore, multicollinearity is not a problem for these data. Hence there is no need to consider eliminating any questions at this stage.

4.1.3 KMO and Bartlett's test

Output 2 below shows the output: the Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity. The KMO statistic varies between 0 and 1. A value of 0 indicates that the sum of partial correlations is large relative to the sum of correlations, indicating diffusion in the pattern of correlations (hence, factor analysis is likely to be inappropriate). A value close to 1 indicates that patterns of correlations are relatively compact and so factor analysis should yield distinct and reliable factors.

Kaiser (1974) recommends accepting values greater than 0.5 as acceptable (values below this should lead you to either collect more data or rethink which variables to include). For these data the value is 0.817, we should be confident that factor analysis is appropriate for these data.

Bartlett's measure tests the null hypothesis that the original correlation matrix is an identity matrix. For factor analysis to work we need some relationships between variables and if the R-matrix were an identity matrix then all correlation coefficients would be zero. Therefore, we want this test to be significant (i.e. have a significance value less than 0.05). A significant test tells us that the R-matrix is not an identity matrix; therefore, there are some relationships between the variables we hope to include in the analysis. For this data, Bartlett's test is highly significant ($p < 0.001$), and therefore factor analysis is appropriate.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**0.817**
Bartlett's Test of Sphericity	**Approx. Chi-Square**	**1625.579**
	df	**136**
	Sig.	**.000**

Output 1:

4.1.4 Eigenvalues

In output 3 below the list eigenvalues associated with each linear component (factor) before extraction, after extraction and after rotation are shown. The eigenvalues associated with each factor represent the variance explained by that particular linear component.

The fig also displays the eigenvalues in terms of the percentage of variance explained (so, factor 1 explains 33.524% of total variance). It should be clear that the first few factors explain relatively large amounts of variance (especially factor 1) whereas subsequent factors explain only small amounts of variance.

In the column labelled *Extraction Sums of Squared Loadings*. The values in this part of the table are the same as the values before extraction, except that the values for the discarded factors are ignored (hence, the table is blank after the third factor).

In the final part of the table (labelled *Rotation Sums of Squared Loadings), the eigenvalues of the factors after rotation* are displayed. Rotation has the effect of optimizing the factor structure and one consequence for these data is that the relative importance of the four factors is equalized. Before rotation, factor 1 accounted for considerably more variance than the remaining two (33.524% compared to 9.671%, 8.437**%**and 7.037%), however after extraction it accounts for only 18.553% of variance (compared to 15.701%, 13.804**%** and 10.611% respectively).

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.699	33.524	33.524	5.699	33.524	33.524	3.154	18.553	18.553
2	1.644	9.671	43.194	1.644	9.671	43.194	2.669	15.701	34.254
3	1.434	8.437	51.632	1.434	8.437	51.632	2.347	13.804	48.058
4	1.196	7.037	58.669	1.196	7.037	58.669	1.804	10.611	58.669
5	0.978	5.754	64.423						
6	0.871	5.122	69.545						
7	0.823	4.844	74.389						
8	0.774	4.555	78.944						

9	**0.645**	**3.794**	**82.739**						
10	**0.573**	**3.373**	**86.111**						
11	**0.548**	**3.226**	**89.337**						
12	**0.475**	**2.792**	**92.129**						
13	**0.412**	**2.423**	**94.552**						
14	**0.346**	**2.034**	**96.586**						
15	**0.276**	**1.625**	**98.211**						
16	**0.157**	**0.924**	**99.135**						
17	**0.147**	**0.865**	**100**						
Extraction Method: Principal Component Analysis.									

Output 3:

4.1.5 Communalities

Output 4 below shows the table of communalities before and after extraction. Principal component analysis works on the initial assumption that all variance is common; therefore, before extraction the communalities are all 1. The communalities in the column labelled *Extraction* reflect the common variance in the data structure. So, for example, we can say that 59.3% of the variance associated with *Lack of explicit policy* is common, or shared, variance.

Another way to look at these communalities is in terms of the proportion of variance explained by the underlying factors. After extraction some of the factors are discarded and so some information is lost. The amount of variance in each variable that can be explained by the retained factors is represented by the communalities after extraction.

The output also shows the component matrix before rotation. This matrix contains the loadings of each variable onto each factor. By default SPSS displays all loadings; however, we requested that all loadings less than 0.5 be suppressed in the output and so there are blank spaces for many of the loadings.

Communalities		
	Initial	Extraction
Lack_of_explicit_policy	1	0.593
Lack_of_finance	1	0.616
Lack_of_technically_trained_manpower	1	0.63
Quality_of_technically_trained_manpower	1	0.715
Hierachical_organizations	1	0.524
Brain_drain	1	0.342
Lack_of_competition	1	0.545
Lack_of_demanding_customers	1	0.741
Lack_of_innovative_customers	1	0.722
Lack_of_high_resolution_regulations	1	0.354
Knowledge_gap	1	0.543
Organizational_rigidities	1	0.612
High_innovation_costs	1	0.44
Excessive_perceived_econ_risks	1	0.644
Restrictive_govt_regulations	1	0.534
Access_to_ICT	1	0.723
ICT_capacity	1	0.696
Extraction Method: Principal Component Analysis.		

Output 4:

Component Matrix[a]

	Component			
	1	2	3	4
Knowledge_gap	0.716			
Access_to_ICT	0.683			
Quality_of_technically_trained_manpower	0.68			
ICT_capacity	0.666			
Organizational_rigidities	0.655			
Lack_of_technically_trained_manpower	0.648			
Restrictive_govt_regulations	0.621			
Hierachical_organizations	0.598			
Lack_of_high_resolution_regulations	0.587			
Excessive_perceived_econ_risks	0.554			
Lack_of_competition	0.533			
Brain_drain	0.52			
High_innovation_costs				
Lack_of_demanding_customers		0.698		
Lack_of_innovative_customers	0.536	0.629		
Lack_of_explicit_policy				
Lack_of_finance				

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

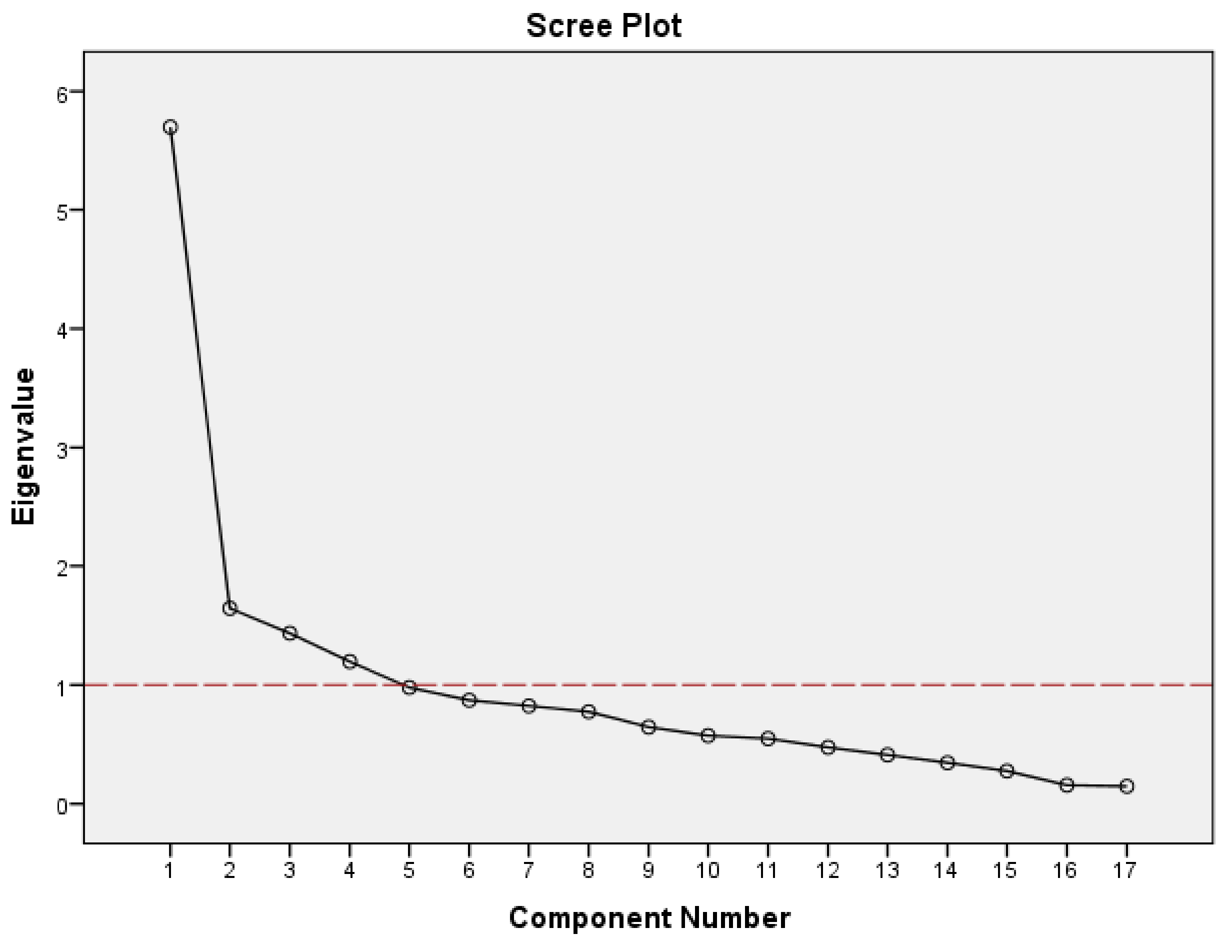
Output 4:

4.1.6 Factors

SPSS has extracted four factors. Factor analysis is an exploratory tool and so it should be used to guide the researcher to make various decisions. One important decision is the number of factors to extract. By Kaiser's criterion we should extract four factors. However, this criterion is accurate when there are less than 30 variables and communalities after extraction are greater than 0.7 or when the sample size exceeds 250 and the average communality is greater than 0.6.

Another way of determining the number of factors to extract is by using the *Scree plot*. The scree plot is shown in Output 5 with a thunderbolt indicating the point of inflexion on the curve. The curve begins to tail off after four factors, before a stable plateau is reached. Therefore, we could probably justify retaining four factors.

- ❖ *If there are less than 30 variables and communalities after extraction are greater than 0.7 or if the sample size exceeds 250 and the average communality is greater than 0.6 then retain all factors with Eigen values above 1 (Kaiser's criterion).*
- ❖ *If none of the above apply, a Scree Plot can be used when the sample size is large (around 300 or more cases).*



Output 5:

4.1.7 Rotated Component Matrix

Output 6 shows the rotated component matrix (also called the rotated factor matrix in factor analysis) which is a matrix of the factor loadings for each variable onto each factor. This matrix contains the same information as the component matrix in Output 4 except that it is calculated after rotation. There are several things to consider about the format of this matrix. First, factor loadings less than 0.5 have not been displayed because we asked for these loadings to be suppressed. Second, the variables are listed in the order of size of their factor loadings because we asked for the output to be *Sorted* by size.

Compare this matrix with the unrotated solution. Before rotation, most variables loaded highly onto the first factor. However, the rotation of the factor structure has clarified things considerably: there are four factors and variables load on the four factors. The suppression of loadings less than 0.5 and ordering variables by loading size also makes interpretation considerably easier (because you don't have to scan the matrix to identify substantive loadings).

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
Quality_of_technically_trained_manpower	**0.797**			
Access_to_ICT	**0.774**			
ICT_capacity	**0.75**			
Lack_of_technically_trained_manpower	**0.712**			
Knowledge_gap	**0.526**			
Lack_of_high_resolution_regulations				
Excessive_perceived_econ_risks		**0.763**		
Organizational_rigidities		**0.714**		
Hierachical_organizations		**0.66**		
Restrictive_govt_regulations		**0.652**		
Lack_of_demanding_customers			**0.848**	
Lack_of_innovative_customers			**0.816**	
Lack_of_competition			**0.669**	
Brain_drain				
Lack_of_finance				**0.766**
Lack_of_explicit_policy				**0.741**
High_innovation_costs				**0.504**
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
a. Rotation converged in 6 iterations.				

Output 6:

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

The study found that 4 latent factors could be used to explain the factor affecting the National System of Innovation. Quality of technically trained manpower, access to ICT, ICT capacity, Lack of technically trained manpower and Knowledge gap formed the first factor (**poor human capital).** Excessive perceived economic risks, organizational rigidities, hierarchical organizations and restrictive government regulations formed the second factor **(regulatory Indiscipline).** Lack of demanding customers, lack of innovative customers and lack of competition formed the third factor **(Undemanding custom).** Lack of finance, Lack of explicit policy and High innovation costs formed the forth factor **(Regulatory Risks).**

It is recommended that further research (regression analysis) be done on the four factors to determine the extent at which each of them affect the National Systems of Innovation.

REFERENCES

[1] Avermaete, T., Viaene, J., Morgan, E.J., Crawford, N., (2003), *"Determinants of Innovation in Small Food Firms"*, European Journal of Innovation Management, Volume 6, No 1, p.p. 8-17.

[2] Baerz, A.M., et al. 2010. Exploring of the Role and Position of Institutional Actors in the University-industry Interactions, *World Applied Sciences J., 11(11): 1432-1438.*

[3] Balzat, M. and Hanusch, H. (2004), Recent trends in the research on national systems of innovation, *Journal of Evolutionary Economics*, 14: 197-210.

[4] Chaminade, C., Intarakumnerd, P. and Sapprasert, K. 2008. Measuring systematic failures in innovation systems in developing countries using innovation survey data: the case of Thailand. Presented at the Globelics Conference, September 2008, Mexico.

[5] Damanpour, F. (1991). Organizational Innovation: a meta-analysis of effects of determinates. *Academy of Management Journal*, 34, 555–591.

[6] Edquist, C. (2001). Systems of innovation for development. Background paper for Chapter 1: "Competitiveness, Innovation and Learning: Analytical Framework" for the UNIDO World Industrial Development Report (WIDR), 2001.

[7] Efstathiades A, Boustras G, *et al.* Factors Affecting the Innovation Process in the Cypriot Food and Beverage Industry, *European Research Studies*, Volume X, Issue (1-2) 2007.

[8] Ella Miron, Miriam Erez and Eitan Naveh, (2004)" Do personal characteristics and cultural values that promote innovation, quality, and efficiency compete or complement each other?", *Journal of Organizational Behavior,*25, 175–199.

[9] Freeman, C. (1995), "The National Innovation Systems in historical perspective", in *Cambridge Journal of Economics*, vol. 19, no. 1.

[10] Frenkel, A. (2003), ‘’Barriers and Limitations in the Development of Industrial Innovation in the Region’’, *European Planning Studies*, Vol.11, pp.115-137

[11] Hadjimanolis, A. (1999), “Barriers to innovation for SMEs in a small less developed country (Cyprus)”, *Technovation*, Vol.19, pp. 561-570.

[12] José Molero Zayas & Antonio García, 2008. "Factors affecting innovation revisited," Working Papers del Instituto Complutense de Estudios Internacionales 05-08, Universidad Complutense de Madrid, Instituto Complutense de Estudios Internacionales.

[13] Koudou C.A. (2011), Examination of the key factors in organization generation of innovation, *Global Conference on Innovations in Management,* London, UK.

[14] Lundvall, B.-Å. (1988), “Innovation as an interactive process: From user-producer interaction to the National Innovation Systems”, in Dosi, G., Freeman, C., Nelson, R.R., Silverberg, G. and Soete, L., (eds.), *Technology and economic theory*, London, Pinter Publishers.

[15] Lundvall, B.-A. (ed.) 1992. National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning, London, Pinter

[16] Nelson, R.R. (ed.) (1993), *National Innovation Systems: A Comparative Analysis*, Oxford, Oxford University Press.

[17] Nebojša Zakic, Ana Jovanovic, Milan Stamatovic, (2008), ‘’External and Internal factors affecting the product and business process innovation***”,*** *Economics and Organization*, Vol. 5, No 1, pp. 17 – 29.

[18] Renate Lukjanska, Internal and external innovation hindering obstacles at sme.

[19] Seyed Abbas Mousavi Tatfi. (2011).The Factors Hindering Innovation at Iranian Smes, *World Applied Sciences Journal* 14 (11*):* 1635-1641.

[20] Yam, R.C.M., Lo, W., Tang, E.P.Y., Lau, A.K.W., 2011. Analysis of sources of innovation, technological innovation capabilities, and performance: an empirical study of
Hong Kong manufacturing industries. Research Policy 40 (3), 391-402.

[21] Zairi, M., (1995), *"Benchmarking innovation best practice",* World class design to Manufacture, Volume 2, No.3, p.p. 33-40.

APPENDIX

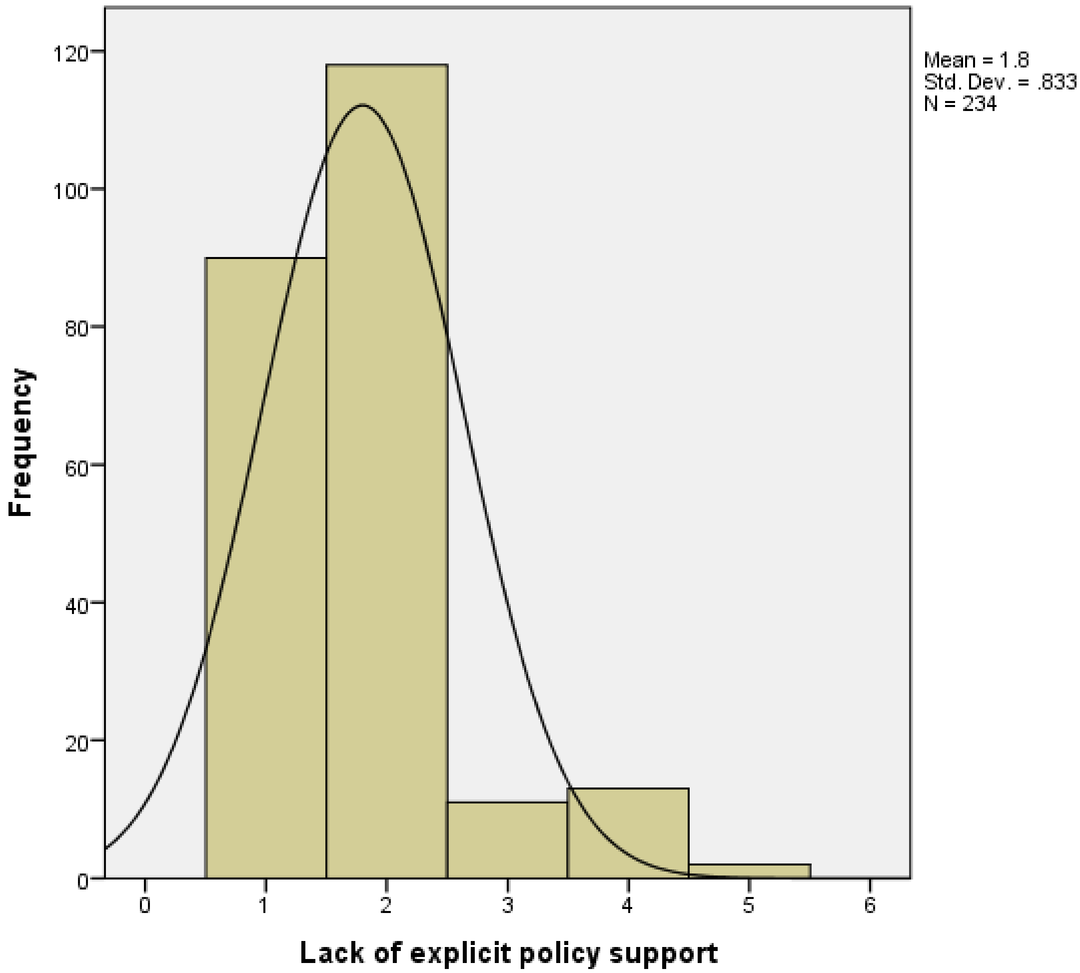
Appendix 1:

		Lack_of_explicit_policy	Lack_of_finance	Lack_of_technically_trained_manpower	Quality_of_technically_trained_manpower	Hierachical_organizations	Brain_drain	Lack_of_competition	Lack_of_demanding_customers	Lack_of_innovative_customers
Correlation	Lack_of_explicit_policy	1.000	.431	.130	.165	.231	.098	.091	-.022	.068
	Lack_of_finance	.431	1.000	.161	.148	.161	.203	.126	.131	.147
	Lack_of_technically_trained_manpower	.130	.161	1.000	.806	.420	.304	.299	.157	.236
	Quality_of_technically_trained_manpower	.165	.148	.806	1.000	.341	.298	.296	.196	.287
	Hierachical_organizations	.231	.161	.420	.341	1.000	.278	.167	.207	.275
	Brain_drain	.098	.203	.304	.298	.278	1.000	.341	.289	.260
	Lack_of_competition	.091	.126	.299	.296	.167	.341	1.000	.416	.423
	Lack_of_demanding_customers	-.022	.131	.157	.196	.207	.289	.416	1.000	.669
	Lack_of_innovative_customers	.068	.147	.236	.287	.275	.260	.423	.669	1.000

	Lack_of_high_resolution_regulations	.239	.198	.284	.366	.253	.198	.345	.210	.351
	Knowledge_gap	.163	.169	.446	.464	.341	.344	.339	.236	.316
	Organizational_rigidities	.236	.201	.276	.257	.480	.295	.254	.178	.287
	High_innovation_costs	.251	.297	.215	.210	.171	.206	.213	.145	.214
	Excessive_perceived_econ_risks	.173	.223	.287	.208	.424	.181	.130	.246	.264
	Restrictive_govt_regulations	.155	.116	.307	.356	.394	.201	.315	.285	.248
	Access_to_ICT	.250	.216	.385	.494	.307	.322	.264	.158	.187
	ICT_capacity	.279	.216	.353	.459	.306	.311	.260	.152	.163

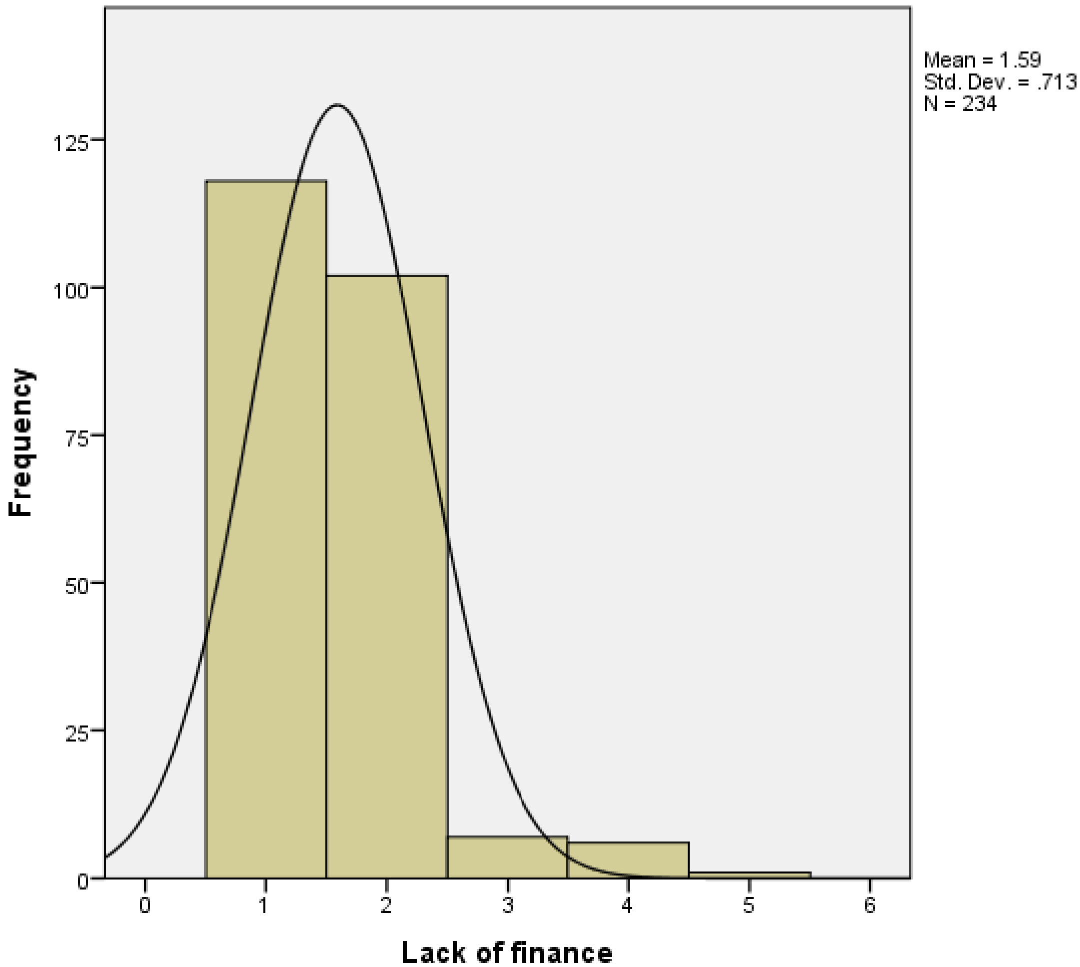
a. Determinant = .001

Appendix 2:

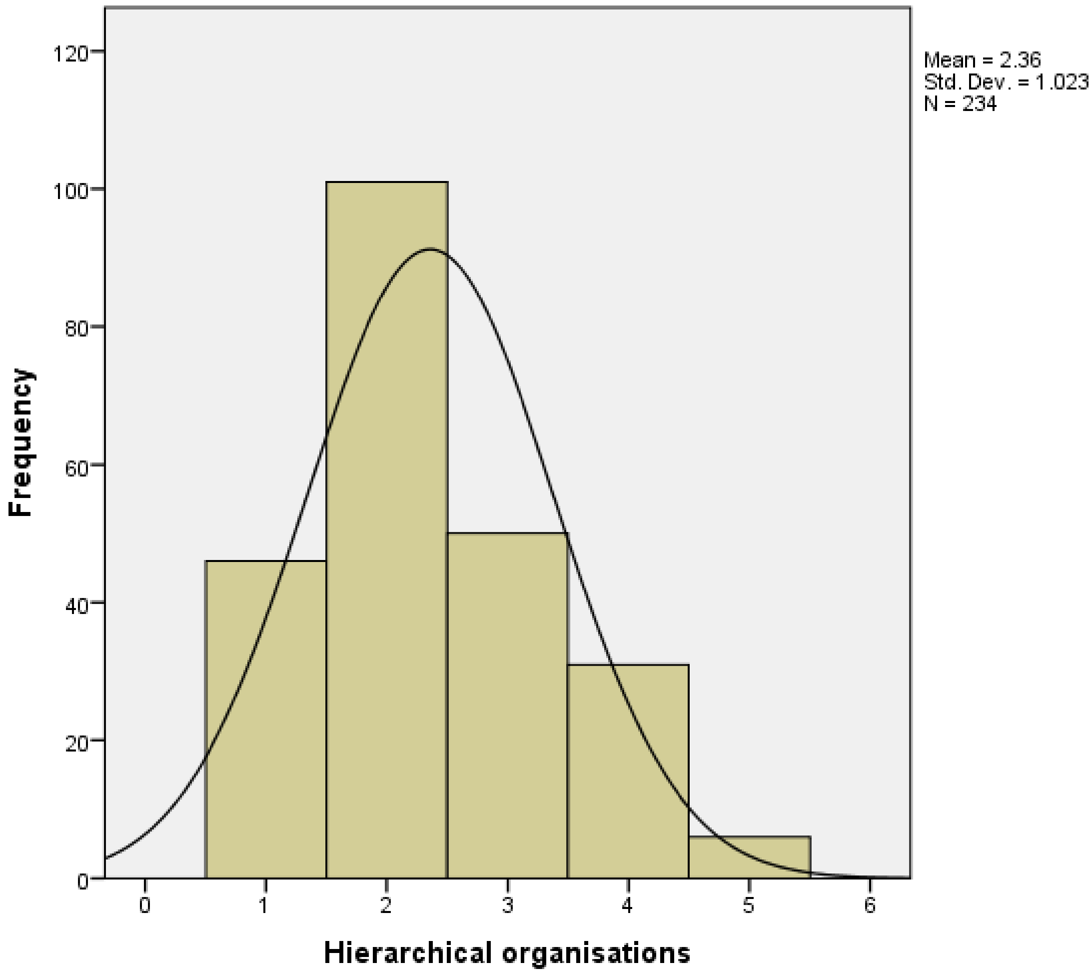


Mean = 1.8
Std. Dev. = .833
N = 234
Frequency
120
100
80
60
40
20
0
0
1
2
3
4
5
6
Lack of explicit policy support

Appendix 3:

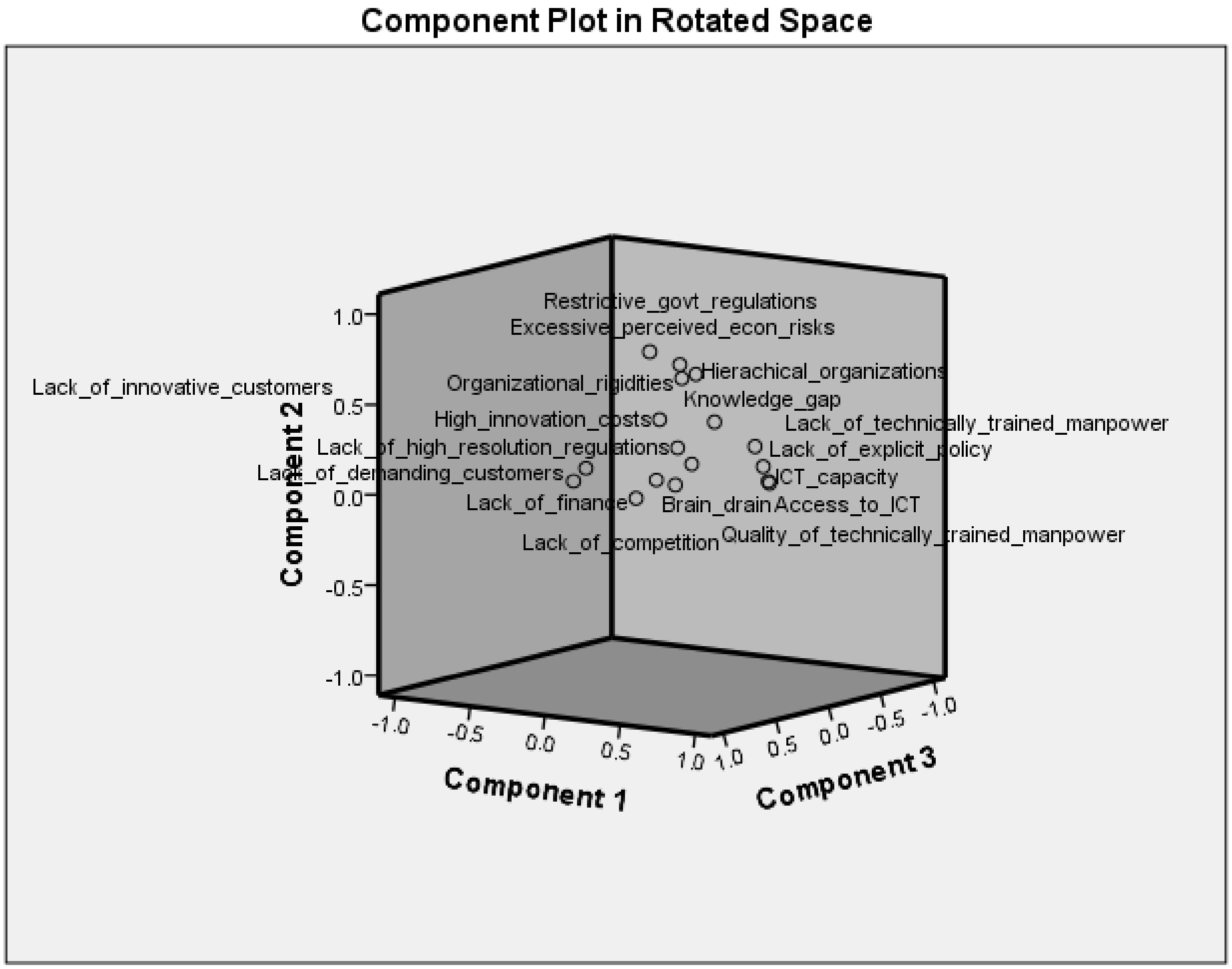

Mean = 1.59
Std. Dev. = .713
N = 234
Frequency
125
100
75
50
25
0
0
1
2
3
4
5
6
Lack of finance

Appendix 4:



Mean = 2.36
Std. Dev. = 1.023
N = 234
Frequency
120
100
80
60
40
20
0
0
1
2
3
4
5
6
Hierarchical organisations

Appendix 5:



Appendix 6:

Component Transformation Matrix

Component	1	2	3	4
1	.630	.564	.434	.309
2	-.364	.018	.820	-.442
3	-.678	.407	.019	.612
4	.102	-.718	.373	.579

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Appendix 7:

Component Score Coefficient Matrix

	Component			
	1	2	3	4
Lack_of_explicit_policy	-.026	-.049	-.084	.467
Lack_of_finance	-.079	-.114	.059	.500
Lack_of_technically_trained_manpower	.277	.043	-.059	-.193
Quality_of_technically_trained_manpower	.327	-.046	-.028	-.159
Hierachical_organizations	-.007	.323	-.097	-.101
Brain_drain	.098	-.103	.168	.048
Lack_of_competition	.049	-.145	.331	.003
Lack_of_demanding_customers	-.120	-.051	.448	-.034
Lack_of_innovative_customers	-.108	-.020	.410	-.017
Lack_of_high_resolution_regulations	.043	.026	.096	.063
Knowledge_gap	.129	.112	.005	-.068
Organizational_rigidities	-.075	.337	-.071	.009
High_innovation_costs	-.108	.126	.000	.271
Excessive_perceived_econ_risks	-.183	.406	-.060	.032
Restrictive_govt_regulations	-.021	.308	-.030	-.124
Access_to_ICT	.307	-.149	-.062	.121
ICT_capacity	.295	-.140	-.073	.135

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Component Scores.

Appendix 8:

Component Score Covariance Matrix

Component	1	2	3	4
1	1.000	.000	.000	.000
2	.000	1.000	.000	.000
3	.000	.000	1.000	.000
4	.000	.000	.000	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Component Scores.

Appendix 9:

Descriptive Statistics

	Mean	Std. Deviation[a]	Analysis N[a]	Missing N
Lack_of_explicit_policy	1.80	.833	234	0
Lack_of_finance	1.59	.713	234	0
Lack_of_technically_trained_manpower	2.20	1.130	234	0
Quality_of_technically_trained_manpower	2.19	1.154	234	0
Hierachical_organizations	2.36	1.023	234	0
Brain_drain	1.98	.958	234	0
Lack_of_competition	2.48	1.049	234	0
Lack_of_demanding_customers	2.50	1.053	234	0
Lack_of_innovative_customers	2.44	1.048	234	0
Lack_of_high_resolution_regulations	2.42	1.008	234	0
Knowledge_gap	2.15	.986	234	0
Organizational_rigidities	2.24	.986	234	0
High_innovation_costs	1.89	.816	234	0
Excessive_perceived_econ_risks	2.15	.953	234	0
Restrictive_govt_regulations	2.54	1.073	234	0
Access_to_ICT	2.32	1.034	234	0
ICT_capacity	2.21	1.033	234	0

a. For each variable, missing values are replaced with the variable mean.

Appendix 10:

Shapiro-Wilk Coefficients Table

n =	2	3	4	5	6	7	8	9	10	11	12	13	14
a1	0.7071	0.7071	0.6872	0.6646	0.6431	0.6233	0.6052	0.5888	0.5739	0.5601	0.5475	0.5359	0.5251
a2			0.1677	0.2413	0.2806	0.3031	0.3164	0.3244	0.3291	0.3315	0.3325	0.3325	0.3318
a3					0.0875	0.1401	0.1743	0.1976	0.2141	0.2260	0.2347	0.2412	0.2460
a4							0.0561	0.0947	0.1224	0.1429	0.1586	0.1707	0.1802
a5									0.0399	0.0695	0.0922	0.1099	0.1240
a6											0.0303	0.0539	0.0727
a7													0.0240

n =	15	16	17	18	19	20	21	22	23	24	25	26
a1	0.5150	0.5056	0.4968	0.4886	0.4808	0.4734	0.4643	0.4590	0.4542	0.4493	0.4450	0.4407
a2	0.3306	0.3290	0.3273	0.3253	0.3232	0.3211	0.3185	0.3156	0.3126	0.3098	0.3069	0.3043
a3	0.2495	0.2521	0.2540	0.2553	0.2561	0.2565	0.2578	0.2571	0.2563	0.2554	0.2543	0.2533
a4	0.1878	0.1939	0.1988	0.2027	0.2059	0.2085	0.2119	0.2131	0.2139	0.2145	0.2148	0.2151
a5	0.1353	0.1447	0.1524	0.1587	0.1641	0.1686	0.1736	0.1764	0.1787	0.1807	0.1822	0.1836
a6	0.0880	0.1005	0.1109	0.1197	0.1271	0.1334	0.1399	0.1443	0.1480	0.1512	0.1539	0.1563
a7	0.0433	0.0593	0.0725	0.0837	0.0932	0.1013	0.1092	0.1150	0.1201	0.1245	0.1283	0.1316
a8		0.0196	0.0359	0.0496	0.0612	0.0711	0.0804	0.0878	0.0941	0.0997	0.1046	0.1089
a9				0.0163	0.0303	0.0422	0.0530	0.0618	0.0696	0.0764	0.0823	0.0876
a10						0.0140	0.0263	0.0368	0.0459	0.0539	0.0610	0.0672
a11								0.0122	0.0228	0.0321	0.0403	0.0476
a12									0.0000	0.0107	0.0200	0.0284
a13											0.0000	0.0094

Appendix 11:

Shapiro-Wilk p-values Table

n \ p	0.01	0.02	0.05	0.1	0.5	0.9	0.95	0.98	0.99
3	0.753	0.756	0.767	0.789	0.959	0.998	0.999	1.000	1.000
4	0.687	0.707	0.748	0.792	0.935	0.987	0.992	0.996	0.997
5	0.686	0.715	0.762	0.806	0.927	0.979	0.986	0.991	0.993
6	0.713	0.743	0.788	0.826	0.927	0.974	0.981	0.986	0.989
7	0.730	0.760	0.803	0.838	0.928	0.972	0.979	0.985	0.988
8	0.749	0.778	0.818	0.851	0.932	0.972	0.978	0.984	0.987
9	0.764	0.791	0.829	0.859	0.935	0.972	0.978	0.984	0.986
10	0.781	0.806	0.842	0.869	0.938	0.972	0.978	0.983	0.986
11	0.792	0.817	0.850	0.876	0.940	0.973	0.979	0.984	0.986
12	0.805	0.828	0.859	0.883	0.943	0.973	0.979	0.984	0.986
13	0.814	0.837	0.866	0.889	0.945	0.974	0.979	0.984	0.986
14	0.825	0.846	0.874	0.895	0.947	0.975	0.980	0.984	0.986
15	0.835	0.855	0.881	0.901	0.950	0.975	0.980	0.984	0.987
16	0.844	0.863	0.887	0.906	0.952	0.976	0.981	0.985	0.987
17	0.851	0.869	0.892	0.910	0.954	0.977	0.981	0.985	0.987
18	0.858	0.874	0.897	0.914	0.956	0.978	0.982	0.986	0.988
19	0.863	0.879	0.901	0.917	0.957	0.978	0.982	0.986	0.988
20	0.868	0.884	0.905	0.920	0.959	0.979	0.983	0.986	0.988
21	0.873	0.888	0.908	0.923	0.960	0.980	0.983	0.987	0.989
22	0.878	0.892	0.911	0.926	0.961	0.980	0.984	0.987	0.989
23	0.881	0.895	0.914	0.928	0.962	0.981	0.984	0.987	0.989
24	0.884	0.898	0.916	0.930	0.963	0.981	0.984	0.987	0.989
25	0.888	0.901	0.918	0.931	0.964	0.981	0.985	0.988	0.989
26	0.891	0.904	0.920	0.933	0.965	0.982	0.985	0.988	0.989
27	0.894	0.906	0.923	0.935	0.965	0.982	0.985	0.988	0.990
28	0.896	0.908	0.924	0.936	0.966	0.982	0.985	0.988	0.990
29	0.898	0.910	0.926	0.937	0.966	0.982	0.985	0.988	0.990
30	0.900	0.912	0.927	0.939	0.967	0.983	0.985	0.988	0.990
31	0.902	0.914	0.929	0.940	0.967	0.983	0.986	0.988	0.990
32	0.904	0.915	0.930	0.941	0.968	0.983	0.986	0.988	0.990
33	0.906	0.917	0.931	0.942	0.968	0.983	0.986	0.989	0.990
34	0.908	0.919	0.933	0.943	0.969	0.983	0.986	0.989	0.990
35	0.910	0.920	0.934	0.944	0.969	0.984	0.986	0.989	0.990
36	0.912	0.922	0.935	0.945	0.970	0.984	0.986	0.989	0.990
37	0.914	0.924	0.936	0.946	0.970	0.984	0.987	0.989	0.990
38	0.916	0.925	0.938	0.947	0.971	0.984	0.987	0.989	0.990
39	0.917	0.927	0.939	0.948	0.971	0.984	0.987	0.989	0.991
40	0.919	0.928	0.940	0.949	0.972	0.985	0.987	0.989	0.991
41	0.920	0.929	0.941	0.950	0.972	0.985	0.987	0.989	0.991
42	0.922	0.930	0.942	0.951	0.972	0.985	0.987	0.989	0.991
43	0.923	0.932	0.943	0.951	0.973	0.985	0.987	0.990	0.991
44	0.924	0.933	0.944	0.952	0.973	0.985	0.987	0.990	0.991
45	0.926	0.934	0.945	0.953	0.973	0.985	0.988	0.990	0.991
46	0.927	0.935	0.945	0.953	0.974	0.985	0.988	0.990	0.991
47	0.928	0.936	0.946	0.954	0.974	0.985	0.988	0.990	0.991
48	0.929	0.937	0.947	0.954	0.974	0.985	0.988	0.990	0.991
49	0.929	0.939	0.947	0.955	0.974	0.985	0.988	0.990	0.991
50	0.930	0.938	0.947	0.955	0.974	0.985	0.988	0.990	0.991

Appendix 12:

Factor Scores

FAC1_1	FAC2_1	FAC3_1	FAC4_1
2.43154	-2.82406	2.04135	-1.00612
.49760	.79723	.45934	-.13657
-.33280	-.68783	-1.37663	-.16064
1.59868	1.36549	.17731	-.45522
-.77858	-1.12426	-.08471	.26694
2.62453	.11608	-.95898	-1.26444
-.22265	-.32979	-.43653	.53013
-.82542	-.05041	-.09174	-.50579
-.27241	.61007	.71002	.40637
-.16141	.80167	-.32879	.78586
1.44188	-1.11816	2.48555	-.21114
-.25778	3.14086	-1.34886	-1.51041
.05538	-.42029	-.45010	-.23552
1.15748	.94622	.49756	1.35194
-1.57248	-.49364	-.37799	.45519
-.40007	1.59663	.62712	.49790
-1.32021	.99893	-1.39606	-.19338
-.57336	.55750	-.30484	1.50164
-.34855	-.86637	-1.53208	-1.23697
.85557	-.87355	.40751	-.68423
.21328	.50784	1.45932	-.78367
-1.47969	1.53375	1.90460	-.81098

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