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MANUFACTURING SITE SELECTION IN THE GLOBAL CONTEXT

by

Mahsa Mardikoraem

A Thesis Submitted in
Partial Fulfillment of the
Requirements for the Degree of

Master of Science
in Engineering

at the
The University of Wisconsin-Milwaukee

August 2016

ABSTRACT

MANUFACTURING SITE SELECTION IN THE GLOBAL CONTEXT

by

Mahsa Mardikoraem

The University of Wisconsin-Milwaukee, 2016

Under the Supervision of Associate Professor, Hamid Seifoddini

The decision making regarding global site selection has been always a challenging and strategic problem. Recently, due to the globalization of the problem many new factors such as political, social, regulatory, government, environmental consideration, etc. gained importance in the decision making process. One of the goals in this thesis is to identify the relevant factors in manufacturing site selection and incorporate them into the data analysis. The collection of a wide range of factors that impact the manufacturing site selection problem at a country level, the quantification of these factors, and incorporation of them into the decision making process needs a quantitative, comprehensive, and flexible approach. In this research hundred countries has been considered for factor analysis and classification. To cluster these countries according to their manufacturing site selection attributes, thirty-four frequently cited attributes are chosen. These factors, also, can be quantified with major economic, business, social, political, and environmental metrics. Factor analysis techniques have used to investigate interrelationships between selected attributes. Our analysis showed that some of these factors can be dropped from our data set. Finally, two types of clustering algorithms, Agglomerative Hierarchical and K-means, are employed to classify countries according to their similarity regrading quantified attributes. We have shown that this approach provides a framework to help the decision making regarding manufacturing facility location selection.. . .

To

Beauty,
All over the world...

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ACKNOWLEDGEMENTS

I would first like to thank my thesis advisor Professor.Hamid Seifoddini. The door to Prof. Seifoddini office was always open whenever I ran into a trouble spot or had a question about my research or writing. He consistently allowed this research to be my own work, but steered me in the right the direction whenever he thought I needed it.

I would also like to thank my friend and colleague, Roya Ghorashi. Without her participation, the data collection and providing a rich literature review on the problem could not have been successfully conducted.

Chapter 1

Introduction

The decision making regarding global site selection has been always a challenging and strategic problem. There are many factors affecting the problem of facility location selection. In recent decades, locating manufacturing facilities in foreign countries have been easier. Global site selection can help companies to reduce cost, and increase profit.

Supply Chain Management is a large field of study, uniting concepts and techniques from many disciplines. It focuses on maximizing the value through the supply chain, from raw material to customers. Due to high competition between companies, the need for carrying out research in Supply Chain management exponentially increases. One of the most significant and challenging decisions for companies have always been facility location selection. Especially locating facilities in other countries makes it more difficult and complex decision, having a lot of risk. This is getting a challenging problem for many companies around the world. It needs a large amount of investigation. It has a long-term impact on the competitiveness of companies, and essential future consequences.

In the past, only large size and multinational companies faced with the problem of facility location in the country level. But recently even medium size companies are considering that. So this problem addresses many firms, and by the passage of time they are increasing. Some main reasons for increasing the companies which face with this problem are competition between companies, ease of transportation, and accessibility to world using online networks to share information and data. The options for globalization have increased as well. In the network era people are related to each other, share information, and connect with many gateways. And countries tend to open their borders to international markets.

Historically economic factors such as wages, labor force, workforce development, proximity to market, etc. have been considered for site selection. Today, however, due to the global dimension of the problem not only these traditional factors are looked at differently, but also many new factors such as political stability, social harmony, trade regulations, nature of governments, environmental consideration, etc. are crucial to the decision making about manufacturing site selection. The identification of all relevant factors in manufacturing site selection and incorporation of them into the analysis of site selection problem pose a challenge to scholars in this field. Thanks to the endeavour of a large number of authors in the area of manufacturing facility location selection, there is a substantial body of scholarly work on relevant factors in manufacturing site selection. The solutions to the problem of incorporating these factors into the manufacturing site selection process in an effective and efficient manner, however, are less satisfactory at the present time. The subjective nature of many of the existing solutions and the huge burden of data collection through surveys make these solutions less desirable. The consideration of a wide range of factors that impact the selection of a location for manufacturing operations, the quantification of these factors, and incorporation of them into the decision making process call for a flexible, quantitative, and comprehensive approach to the problem of global manufacturing site selection.

Factor analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors. It is an essential part of any data driven approaches. It has widely used in different research areas seeking various purposes.

Cluster analysis has been widely used in different field of studies for identifying groups of objects according to their common attributes. Many authors have applied cluster analysis based on similarity coefficient measures to improve the design and operation of manufacturing systems (Anderberg 1973); (Seifoddini and Wolfe 1986); (Yon 2006); (Dunn and Everitt 2004); and (Abdelhakim A. et al 2012);(Ghorayshi, Mardikoraem 2016).

In this research an approach is presented to the global manufacturing site selection problem based on factor analysis and cluster analysis. We collected factors affecting global site selection. Then, we analyze factors using factor analysis. This analysis gives us an insight on relations between factors, their importance and their uniqueness. Then we employ two main clustering methods, Hierarchical and k-means.Complete linkage clustering and Euclidean distance coefficient based on manufacturing site selection attributes to classify countries according to their suitability for manufacturing operations. And then k-means clustering as second method has been used.To quantify the manufacturing site selection attributes we choose the existing economic /business indices which closely reflect the relevance of each attributes to the decision on site selection. The availability of sources such as World Bank, United Nations, World Economic Forum, and so on greatly alleviates the burden of data collection through surveying and other methods. The approach to the manufacturing site selection problem presented here provides a flexible, quantitative, and custom made framework for decision making for global manufacturing site selection.

Chapter 2

Litrature Review

The literature review on global manufacturing site selection has been categorized into two parts. The first part includes studies on factors impacting decision making about the global manufacturing facility location selection problem. In the second part, studies on solutions to the problem are reviewed(Ghorashi,Mardikoraem 2016)

2.1 Global facility location factors

A wide range of factors potentially influence corporate decisions to locate production facilities across international boundaries (McCarthy 2003). Bass, McGragor and Walters (1977) proposed some factors including market accessibility, availability of basic services, environmental considerations, site location costs, industrialization, labour and staff availability, host location taxes and incentives, area reputation, the nature of the host government , and the government policies in deriving managements to invest in a foreign country. For their study they use a survey of 118 plants operated by U.S. firms in Latin America, Europe and Asia. Rummel and Heenan (1978) proposed a list of important factors in decision making about the selection of an international industrial location including political risks, domestic instability, foreign conflict, political climate, and economic climate.Tong (1979) surveyed 242 foreign-owned manufacturing firms and identified the followings as the most important factors affecting firms location decisions: transportation services, labor attitudes, space for expansions, proximity to markets, and availability of a site.

Epping (1982) indicated that firms have chosen specific locations based on three major types of factors: availability of transportation facilities for moving raw materials and finished goods, availability of labor, and personal considerations.

Chernotsky (1983) surveyed 21 German and Japanese firms to find the influential factors in their decision making on manufacturing site selection. The results of his study show that availability of sites, desirability of sites for incoming personnel, and market access were the most important considerations. These firms placed less emphasis on labor, financial incentives and access to raw materials and semi-finished goods. Barkley and McNamara (1994) ranked the location factors for companies based on the size of the plant. They claim that depending on the size of the plant the importance of factors may vary.

Badri, Davis and Davis (1995) selected 77 factors based on literature review and used questionnaire approach to explore the impact of factors on the manufacturing site selection. They proposed three models of industrial location analysis complementary to traditional approaches of industrial location analysis.

Chamnong and Colin (1995) examined the design and implementation of a knowledge based decision support system (KBDSS) in the facility location domain in order to develop the list of factors for manufacturing site selection. Their study identified a list of factors which are important for manufacturing facilities in the USA. The list consists of market, transportation, labor, site consideration, raw materials, basic services, utilities, environmental regulations, and communitys environmental concerns for locating a manufacturing facility.

Another study by Kahley (1986) indicated how both foreign and domestic firms in US are influenced by some basic factors. It divided factors into two groups, independent and dependant. Some of these factors are labor (skilled workers, union membership), energy (fuel cost, climate), trade volume, state development efforts, employment rate, market (personal income). Ulgado (1996) surveyed 319 US and foreign manufacturers in the USA. According to his survey some of the factors are state financial assistance, local financial assistance, state tax breaks, local tax breaks, business assistance, employee training, infrastructure development, free trade/enterprise zones, site improvements, site selection assistance, and land grants. This paper also demonstrates that American firms are greatly influenced by financial incentives, while foreign firms are relatively more attracted to non-financial incentives. Based on this study, factors related to communities environmental concerns, logistic factors, and trade concerns are more important for foreign companies while domestic corporations are more influenced by factors such as taxes financial incentives, capital gain laws and so on.

Canel and Khumawala (1996) divided factors into two groups: reactive and proactive.

They defined some quantitative as well qualitative factors and incorporated them into a 0-1 mixed integer programming problem. Canel and Das (2002) in their literature review introduced the most common and influential factors on facility location decision as Labor and other production inputs; political stability; host government attitudes toward foreign investment; host government tax and trade policies; proximity to major markets; access to transportation; and existence of other competitors. They formulated the problem of global facility location using 0-1 mixed integer programming. They concluded that it is prudent for manufacturers to consider their facility location decisions in conjunction with marketing and manufacturing strategies.

McCarthy (2003) employed Delphi study and analysed the existing literature to identify the most significant attributes in manufacturing site selection. They cited costs, infrastructure, labor characteristics, government and political factors, and economic factors as the most influential ones for manufacturing global facility location.

In more recent publications environmental impacts and sustainability factors are more paramount. Chen, Olhager, and Tang (2013) have considered the impact of sustainability on global facility location selection decisions. Their study based on the current literature demonstrates the significance of sustainability attributes in the selection of a global manufacturing site for contemporary corporations.

2.2 Existing Approaches to manufacturing site selection problem

The identification of the most relevant attributes is the first step in finding a solution to the manufacturing facility location selection problem. The second step involves the development of a methodology for effective use of these attributes in the decision making process in order to find a practical and useful solution to the problem. Prior to the introduction of our methodology, a brief survey of the literature on existing solutions to the problem is presented here.

Hoffman and Schniederjans (1994) proposed a 2-stage computer based model using goal programming (GP) software. In the first stage a suitable country is determined. Countries Optimal Performance Factors (OPFs) are selected and weighted for each country, then trade-off information about each is entered in GP model to determine which country provides the best circumstance for global expansion. In the second stage the best available facility site in that country is selected. In a case study for the selection of a production facility for a US brewery, twenty potential European countries are evaluated based on thirteen criteria to determine which site should be chosen.

Onut and Soner (2007) used fuzzy TOPSIS approach to determine the best solid waste transhipment site. They also employed fuzzy AHP for determining weighting factors. They applied TOPSIS approach on ISTAC Company in Istanbul to find the best location for solid waste among five candidate sites by using three defined objectives and fuzzy linguistic variables. Vahidnia, Alesheikhi, and Alimohammadi (2009) combined Geographical Information System (GIS) analysis and Fuzzy AHP for hospital site selection problems to develop a well distributed network of hospitals. Travel time, distance from arterial routes, population density, land cost, and air pollution are factors used in the decision making matrix.

Levinson (1996) employed a systematic method to measure the impact of state environmental regulations on manufacturing plant location. He considered six environmental regulatory measures as well as eleven independent variables and incorporated them in a conditional logic model of plant location choice to show that the differences in environmental regulation do not considerably affect decision making on the location of manufacturing plants.

Mazzarol and Choo (2003) studied the purchase of industrial real estates by small to medium enterprises using a three stage methodology. In the first stage, discussion guide is prepared based on literature review. In the second stage telephone survey is done based on the sample of 450 firms. In the final stage an expert panel is formed to evaluate the result from survey and its implications.

Canbolat, Chelst and Garg (2005) applied a combination of decision tree and multi-attribute utility theory in three phases to select a country for the purpose of manufacturing facility location. In the first phase they determined location factors as well as uncertainties and relationship among them. In the second phase they used decision tree to reach cumulative risk profile to feed MAUT software to weight the factors and evaluate alternative countries. Finally, they used a hypothetical auto supply company for evaluating potential plant location sites in five countries. Badri (2007) developed 14 dimensions based on literature search and psychometric principles to generate two hundred and five critical industrial locations factors. This methodology is a useful tool which can be employed by foreign investors to evaluate these critical factors for industrial location selection decision making.

Nielson (2011) reviewed the United Nations Development Program country classification system, World Bank country classification system and IMF country classification system which are based on countries' development level. As an alternative to these systems he proposed a new method of developing the classification system [23]. Eterovic and zgl (2012) applied combination of fuzzy AHP and TOPSIS using nineteen factors affecting facility location selection based on strategic objectives in producing rattan material walking support/serving trolley project. They normalized the data for each factor and then applied FAHP to weight them. Then they employed TOPSIS method to rank countries and find the best location.

More recently cluster analysis has been proposed as an approach to the problem of manufacturing facility location selection. Kalantari (2013) in his masters thesis applied average linkage clustering method to classify facility sites based on several site selection factors. He demonstrated his model by a numerical example using generated data. Also Balali et al (2015) have used clustering approach to the problem of manufacturing site selection for the United States. These studies, although limited in scope, indicate that cluster analysis can be used as an effective tool to help manufacturing corporations in the decision making regarding the selection of a suitable site for their manufacturing facilities.

Chapter 3

Factors in Global Facility Location

In this study one hundred countries are considered for analysis. To avoid arbitrary selection of countries, a combination of market size, GDP per capita, quality of lifefactors etc. has been used to choose the top 100 countries. To classify these countries according to their manufacturing site selection factors, thirty-four global factors which are frequently cited in the literature for their importance in manufacturing site selection decisions are chosen. These factors, also, can be quantified with relative ease using major economic, business, social, political, and environmental metrics. Numerical values for these metrics are obtained from main worldwide data sources including: World Bank data base. (http://data.worldbank.org/,www3.weforum.org, http://data.uis.unesco.org/, http://www.ssfindex.com/,http://www.tradingeconomics.com/,http://www.bls.gov/fls/, http://www.worldeconomics.com/,http://knoema.com/atlas/, http://www.compareallcountries.com,http://www.oecdilibrary.org,http://europa.eu/about-eu/facts figures/economy/index). The raw data are then normalized to reflect a common scale. Then, factors are analyzed to remove redundancy and duplications. Consequently, countries are clustered based on real data, normalized values, by employing complete linkage clustering in conjunction with Euclidean distance coefficient and also K-means clustering.A more detailed description of steps in the collection of manufacturing location factors in the country-level is summarized in the following sections.

3.1 Selection of Factors

According to previous studies on manufacturing site selection problems in literature, there are a large number of economic, social, environmental, political factors which significantly influence the decision about manufacturing site selection. Sixty three such factors are illustrated in figure 3.1.

Furthermore we narrow down the number of factors to thirty four based on the followings.

1. Factors which have been widely discussed and frequently cited in the literature.

2. The most distinct factors which best represent the most important characteristics crucial to effectiveness and efficiency of manufacturing operations.

3. Factors which can be quantified with relative ease by using widely popular economic, business, social, political, and environmental metrics in conjunction with used with accessible data sources such as World Bank, United Nations, World Economic Forum. The results of the final selection are presented in figure3.2.

3.2 Data Collection and Analysis

The World Bank database is the main source for numerical values of metrics employed to quantify site selection factors. Some other international surveys and databases are also used to complement the main data as become necessary. To have a common scale for a wide range of data used in the analysis, feature scaling method is used as shown in Equation (1) below.

X= (X-Xmin)/(Xmax-Xmin) (1)

Economic Factors	**Quality of life**	**Infrastructure**	**Labor characteristics**	**Business and industrial factors**	**Market characteristics**	**Environmental factors**	**Political factors**	**Social factors**
Cost of Business	Health Expenditure per capita	Transport Infrastructure	Labor force	Foreign Direct Investment	Lead-time to import	Sustainability	Political stability and absence of violence/terrorism	Religious
GDP	Internet users	On-the-job training	Unemployment	Start-up procedures	Market capitalization	Space for expansion	Government Effectiveness	Language
GDP per Capita	Safety	Research and Development	Wage rate	Time required to start a business	Market size	Climate condition	Regulatory quality	Culture
Inflation	Quality of education	Services	Labor attitude	Business sophistication	Number of trademark applications	Rule of law	Control of corruption	
Lending Interest Rate	Happiness	Robustness	Labor knowledge	Host incentive	Area reputation		Voice and accountability	
Tax rate	Insurance law	Reliability	Union flexibility	Industrialization	Accessibility		Sanctions	
Property Rights	Availability of utilities	Availability of fuels	Motivation	Access to raw material				
Accountability	Quality and reliability of utilities	Quality and reliability of suppliers						
Site cost	Attitude toward business	Proximity to parent company						
Energy cost								
Transportation Cost								
Currency strength vs.US dollar								

FIGURE 3.1: Factors used in the literature for Manufacturing Site Selection

Economic Factors	**Quality of life**	**Infrastructure**	**Labor characteristics**	**Business and industrial factors**	**Market characteristics**	**Environmental factors**	**Political factors**
Cost of Business	Health Expenditure per capita	Transport Infrastructure	Labor force	Foreign Direct Investment	Lead-time to import	Sustainability	Political stability and absence of violence/terrorism
GDP	Internet users	On-the-job training	Unemployment	Start-up procedures	Market capitalization		Government Effectiveness
GDP per Capita	Safety	Research and Development	Wage rate	Time required to start a business	Market size		Regulatory quality
Inflation	Quality of education	Services		Business sophistication	Number of trademark applications		Control of corruption
Lending Interest Rate					Accessibility		Voice and accountability
Tax rate							
Property Rights							
Accountability							

Figure 3.2: Factors used in this research for Manufacturing Site Selection

Chapter 4

Factor Analysis

Factor analysis is a statistical method to find some latent variables. Number of latent variables is less than number of observed factors. This method is used to show variability between correlated observed factors. It is an essential part of any data driven approaches. It has widely used in different research areas. Brush (1991) did the factor analysis using the principal components method with varimax rotation in order to find factors which have similar importance to the location decision. Factor Analysis can be used for different reasons. It can be used as a data reduction tool. Data analysis and finding patterns is getting more complex with a large number of variables. In addition, interpret data with less number of variables is easier. At a same time reducing variables blindly can remove important and effective variables from our study. In some cases, factor analysis is used to remove redundancy or duplication from a set of correlated variables. In many data analysis project, there are many variables which are correlated. Without factor analysis, correlation would be affected further analysis results. Factor analysis can represent correlated variables with a smaller set of variables. This application have used a lot in psychology and social sciences. Factor analysis give relatively independent variables which will certify that correlation among factors will not affect further analysis.

4.1 Factor Analysis

Correlation matrix between observed factors showed high correlation between some of factors. This confirms the necessity of factor analysis for this problem. Some of factors in one category, for example political factors, are correlated with each other. Or even some factors from different categories have high correlation. For example number of trademark applications and labor force have high correlation. Therefore, any interpretations before factor analysis can be misleading.

4.1.1 Factor Analysis Model

If the observed variables are X1, X2 . Xn, the common factors are F1, F2 Fm and the unique factors are U1, U2 Un , the variables may be expressed as linear functions of the factors:

$X_1 = \lambda_{11}F1 + \lambda_{12}F2 + \lambda_{13}F3 + \ + \lambda_{1m}Fm + \lambda_1 U_1$

$X_2 = \lambda_{21}F1 + \lambda_{22}F2 + \lambda_{23}F3 + \ + \lambda_{2m}F_m + \lambda_2 U_2$

.....

$X_n = \lambda_{n1}F1 + \lambda_{n2}F2 + \lambda_{n3}F3 + \ + \lambda_{nm}Fm + \lambda_n Un$

$\lambda_i U_i = e_i$

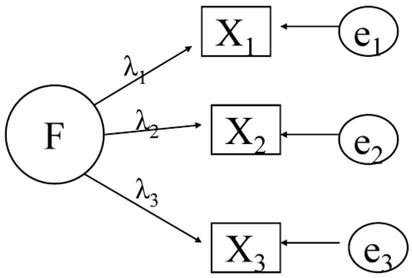

FIGURE 4.1: Factor Analysis Model

Factor analysis seeks to find the coefficients $\lambda_{11}, \lambda_{12}\lambda_{nm}$ which best reproduce the observed variables from the factors. The coefficients $\lambda_{11}, \lambda_{12}\lambda_{nm}$ are weights in the same way as regression coefficients (because the variables are standardised, the constant is zero). For example, the coefficient λ_{11} shows the effect on variable X1 of a one-unit increase in F_1. In factor analysis, the coefficients are called loadings and, when the factors are uncorrelated, they also show the correlation between each variable and a given factor. In the model above, a11 is the loading for variable $X_1 on F_1, \lambda_{23}$is the loading for variable $X_2 on F_3$, etc.

4.1.2 Assumptions of Factor Analysis Model

Measurement error has constant variance and is, on average, 0.

$$Var(e_j) = \sigma_j^2 \quad E(e_j) = 0$$

No association between the factor and measurement error

$$Cov(F, e_j) = 0$$

No association between errors:

$$Cov(ej, e_k) = 0$$

Local (i.e. conditional independence): Given the factor, observed variables are independent of one another.

$$Cov(X_j, X_k|F) = 0$$

Consider matrix λ: Columns in this matrix show derived factors and rows show input variables. Loadings represent degree to which each of the variables correlates with each of the factors. Loadings range is from -1 to 1. Inspection of factor loadings reveals extent to which each of the variables contributes to the meaning of each of the factors. High loadings provide meaning and interpretation of factors.

4.1.3 Commonalities

The communality of X_j is the proportion of the variance of X_j explained by the m common factors:

$$Comm(X_j) = \sum \lambda_{ij}^2$$

It actually is sum of squared multiple correlations between X_j and the factors.

$$Uniqueness(X_j) = 1 - Comm(X_j)$$

When communality is high or uniqueness is low, X_j is informative,

variables with high communality share more in common with the rest of the variables.

4.1.4 Factor Analysis Results

The most extreme countries are the most segregated ones in terms of variables. In table 4.1 seven most extreme countries have been shown. In fact, these countries can be assumed as outliers for used data set. These countries have extreme characteristics compare to other countries. Finding them and consider their effects in our further analysis will be shown useful.

TABLE 4.1: The most extreme countries

	Countries
1	Unites States
2	China
3	India
4	Venezuela
5	Lebanon
6	Iran
7	Qatar

Figures (top and right view) for factor analysis with three latent variables have been shown in the graph 4.2. The axis for these graphs are latent variables.

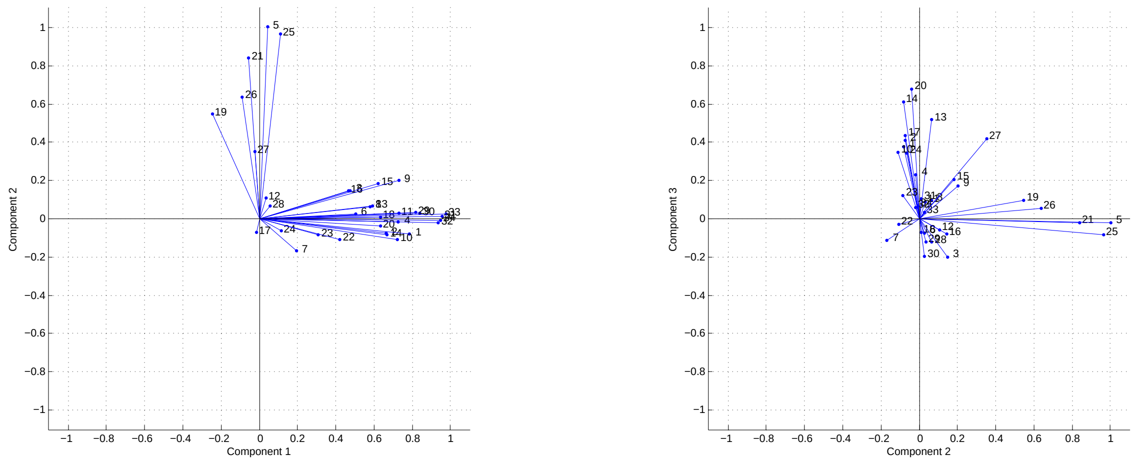

FIGURE 4.2: Factor Analysis with three components

Figure 4.2 shows how observed factors can be written approximately as a linear function of latent variables.

loadings (correlation among factors and components) and the commonalities (1-uniqueness) for three factors have been shown in the figure 4.3.

The values under 0.3 are substituted by 0. Because values under 0.3 show very small correlation and they can be ignored.

by comparing log likelihood values for different number of components, factor analysis with 5 number of variables is chosen. Loadings (correlation among factors and components) and the commonalities (1-uniqueness) for five factors have been shown in the figure 4.4.

Some interpretations from shown results are:

Safety and Sustainability have very small correlations with latent components. and their commonality values are low. These facts also could be concluded by considering correlation matrix. In correlation matrix Safety and Sustainability are two factors that have very small correlation with other factors.In addition, intuitively can be justified as well. Sustainability is the only factor in the environmental category. Safety factor is not dependent on other factors as well.

There is a latent factor which has high correlation with most of Economic, Political, and quality of life factors, except tax rate and safety. Most of these observed factors have high commonality. It seems that these observed factors can be segregated among developed and undeveloped countries.

GDP and Market Capitalization have high values of loading with a latent variable.There is a high correlation between them. We dropped one of them from our data set. Because the second one does not give us more information.

Number of trademark applications and Labor force are highly correlated with one of the latent variables. So we may drop one of the variables.

All political variables except Voice and Accountability are highly correlated with only one of latent variables. So with keeping only one of them in our data set, we do not lose much information.

Tax rate and Service are highly correlated with one of latent components.

After these observations, some of the factors are dropped. It is important to consider that there is no best solution in factor analysis. Reducing number of variables even those that are highly correlated may cause losing information. Therefore, the goal is seeking a trade off between losing information and removing correlation.

We dropped Accountability, GDP Per Capita, Internet Users, Market Capitalization, Number of Trademark Applications, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption factors.

Factors	Category	Comp1	Comp2	Comp3	Communality
property rights	Economic	0.78	0	0.37	0.82
Accountability	Economic	0.66	0	0.41	0.66
Cost of business	Economic	0.47	0	0	0.24
GDP Per Capita	Economic	0.72	0	0	0.63
GDP	Economic	0	1	0	0.99
Inflation	Economic	0.5	0	0	0.24
Tax rate	Economic	0	0	0	0.08
Lending Interest rate	Economic	0.57	0	0	0.37
Health Expenditure per capita	Quality of life	0.73	0	0	0.7
Education	Quality of life	0.72	0	0.34	0.69
Internet users	Quality of life	0.73	0	0	0.5
Safety	Quality of Life	0	0	0	0.01
Transport infrastructure	Infrastructure	0.59	0	0.51	0.76
On-the-job training	Infrastructure	0.66	0	0.61	0.9
R &D	Infrastructure	0.62	0	0	0.56
Services	Infrastructure	0.46	0	0	0.23
Unemployment	Labor char	0	0	0.43	0.16
Wage Rate	Labor char	0.63	0	0	0.39
Labor Force	Labor char	0	0.54	0	0.38
Business sophistication	Business Factors	0.63	0	0.67	0.97
FDI	Business Factors	0	0.83	0	0.68
Start-Up Processors	Business Factors	0.42	0	0	0.18
Time required to start a business	Business Factors	0.3	0	0	0.11
Lead-time to import	Market Char	0	0	0.34	0.12
Market Capitalization	Market Char	0	0.96	0	0.89
N trademark applications	Market Char	0	0.63	0	0.43
Market Size	Market Char	0	0.35	0.42	0.43
sustainability	Environmental	0	0	0	0.01
Voice and Accountability	Political factors	0.81	0	0	0.65
Political Stability and Absence of Violence/Terrorism	Political factors	0.83	0	0	0.68
Government Effectiveness	Political factors	0.95	0	0	0.95
Regulatory Quality	Political factors	0.93	0	0	0.89
Rule of Law	Political factors	0.97	0	0	0.96
Control of Corruption	Political factors	0.94	0	0	0.92

FIGURE 4.3: Loadings and Uniqueness values for three latent factors

Factors	Category	Comp1	Comp2	Comp3	Comp4	Comp5	Communalities
Property rights	Economic	0.87	0	0	0	0	0.88
Accountability	Economic	0.71	0	0	0	0	0.68
Cost of business	Economic	0.53	0	0	0	0	0.34
GDP Per Capita	Economic	0.73	0	0	0	0	0.66
GDP	Economic	0	0	0.83	0	0	0.99
Inflation	Economic	0.51	0	0	0	0	0.25
Tax rate	Economic	0	0	0	0	-0.41	0.31
Lending Interest rate	Economic	0.63	0	0	0	0	0.45
Health Expenditure per capita	Quality of life	0.64	0	0	0	0	0.74
Education	Quality of life	0.78	0	0	0	0	0.69
Internet users	Quality of life	0.71	0	0	0	0	0.60
Safety	Quality of Life	0	0	0	0	0	0.03
Transport infrastructure	Infrastructure	0.67	0	0	0.45	0	0.80
On-the-job training	Infrastructure	0.71	0	0	0.57	0	0.90
R &D	Infrastructure	0.61	0	0	0	0	0.59
Services	Infrastructure	0	0	0	0	0.53	0.46
Unemployment	Labor char	0	0	0	0.37	0	0.18
Wage Rate	Labor char	0.55	0	0	0	0	0.43
Labor Force	Labor char	0	0.99	0	0	0	0.88
Business sophistication	Business Factors	0.66	0	0	0.67	0	0.99
FDI	Business Factors	0	0.74	0.33	0	0	0.88
Start-Up Processors	Business Factors	0.4	0	0	0	0	0.20
Time required to start a business	Business Factors	0.29	0	0	0	0	0.13
Lead-time to import	Market Char	0	0	0	0.34	0	0.15
Market Capitalization	Market Char	0	0	1	0	0	0.96
N trademark applications	Market Char	0	0.92	0	0	0	0.83
Market Size	Market Char	0	0	0	0.44	0	0.48
sustainability	Environmental	0	0	0	0	0	0.01
Voice and Accountability	Political factors	0.73	0	0	0	0.7	0.99
Political Stability and Absence of Violence/Terrorism	Political factors	0.82	0	0	0	0	0.69
Government Effectiveness	Political factors	0.98	0	0	0	0	0.96
Regulatory Quality	Political factors	0.94	0	0	0	0	0.90
Rule of Law	Political factors	0.98	0	0	0	0	0.97
Control of Corruption	Political factors	0.96	0	0	0	0	0.93

FIGURE 4.4: Loadings and Uniqueness values for five latent factors

Chapter 5

Clustering

Finding the best generic solution to the problem of manufacturing facility location selection may not be practical due to the complexity of the problem and the dynamic nature of political, social, environmental as well as manufacturing systems. This is true because the best solution is different for each industry and even in the same industries, the best solution may vary according to the firms vision and competitive strategies. Thus, the selection of the best solution for the manufacturing site selection problems is not a realistic goal, unless special circumstances of the company, industry, and products are determined first. For this reason we employ clustering approach to the problem. The formulation of the problem as a clustering problem provides several advantages as follows.

1. Cluster analysis is suitable for data mining on a large volume of data and this is very important in the decision making regarding manufacturing site selection.

2. The flexibility of having a frame work based on a number of alternative sites which can be further evaluated using more specific considerations for an individual corporation

is another advantage of the proposed model.

3. The utilization of widely used international metrics for quantification of economic, business, social, political, and environmental factors greatly facilitate the evaluation process and significantly improve the effectiveness of the solution to the site selection problem. Use of indices such as gross national products-GDP, human development index-HDI, global competitiveness index-GPI in conjunction with worldwide data bases of World Bank, United Nations and other agencies are crucial to real world applications of manufacturing site selection solutions.

4. The ability to expand or limit the number of potential sites, based on the selection of a threshold value of the similarity level or Euclidean distance in the clustering algorithm, is another flexibility inherit in the proposed model.

5. The proper choice of site selection factors and fine tuning of their importance coefficients allow the analyst to customize the solution to specific situations.

For these reasons, the proposed methodology offers a flexible, quantitative, and customized framework for the formulation of, data analysis for, and decision making about the problem of manufacturing site selection.

5.0.1 Clustering Methods

Clustering is method of making a group of objects into classes of similar objects. All objects in a cluster can be considered as one object. In cluster analysis, we partition the data set into groups with the most similar characteristics. Clustering unlike classification is an unsupervised learning method. It is adaptable to changes and helps single out features that distinguish various groups.

Fraley (1998) divided the clustering methods into two main groups: hierarchical and partitioning methods. Han (2001) divided the clustering methods into three main categories: density-based methods, model-based clustering and grid based methods. Clustering methods generally can be classified into the following categories:

Hierarchical Method, Grid-Based Method, Model-Based Method, Constraint-based Method, Partitioning Method, and Density-based Method.

5.0.2 Hierarchical Clustering

Hierarchical Clustering creates a hierarchical partitioning of the objects in our data set. Hierarchical clustering methods can be classified into two major types:

- Agglomerative Approach
- Divisive Approach

Agglomerative Approach: Agglomerative Approach or bottom-up approach starts with making groups of individual objects. Then it combines existing clusters at each step.

Divisive Approach: In divisive Approach or top-down approach, we start with one cluster including all objects. Then we split up the cluster into smaller clusters. It continues until each cluster includes only one object.

Among the two types hierarchical clustering algorithms (agglomerative and divisive), the agglomerative clustering algorithms are more promising for the data analysis in our proposed method. We need to define a metric and a linkage criteria. Agglomerative methods include single linkage, average linkage and complete linkage clustering which evaluate all pair-wise distances between groups to generate clusters and sub clusters [27].

The algorithm for agglomerative hierarchical cluster analysis is:

First, make a matrix of objects-attributes. Then find the similarity/dissimilarity between every pair of objects in the matrix (distance between objects). There are different criteria for calculating similarity or dissimilarity between objects.

Second, link pairs of objects regarding similarity coefficient in the previous step. Choose a linkage function to pair objects. Paired objects have been assumed as one new objects. Continue to have one cluster.

Third, determine where to cut the hierarchy tree into clusters. In this step, use the cluster function to prune branches off the bottom of the hierarchical tree. Then all the objects below each cut are considered as a single cluster.

To avoid the chaining problem of single linkage clustering and extra calculation burden of average linkage clustering, we chose complete linkage clustering (Seifoddini 1988) in conjunction with Euclidean distance coefficient to carry out cluster analysis. To illustrate the clusters and sub-clusters graphically and demonstrate the exercise of choices based on the threshold value of the Euclidean distances we use dendograms (Abdelhakim et al 2012).

In this research complete linkage clustering in conjunction with Euclidean distance coefficient is employed to identify groups of countries with similar potentials for manufacturing site selection (Dunn and Everitt 2004). Matlab software is used to carry out the calculations and to obtain clustering results.

Equation (2) shows Euclidean Distance:

$$\| a - b \| = \sqrt{(\sum (a_i - b_i)^2)} \qquad (2)$$

Maximum or complete linkage between two sets of observations A and B is shown in) equation (3).

$$Max(d(a,b) : a \in A, b \in B) \qquad (3)$$

The countries are categorized based on the attributes that impacts manufacturing operations. Using the complete linkage clustering method assure that all countries in each group are at least as similar as the similarity reflected in the threshold value used for the selection of clusters (Anderberg 1973). Also each category shows which factors are playing pivotal role in the inclusion of countries into a particular cluster. This help the decision makers to better incorporate their preferences in the selection process. After dropping some variables in factor analysis,we apply hierarchical clustering to updated data set.

Results(dendogram) for hierarchical clustering using euclidean similarity criteria have been shown in figure 5.1. Two thresholds have been shown in the figure. If we use the

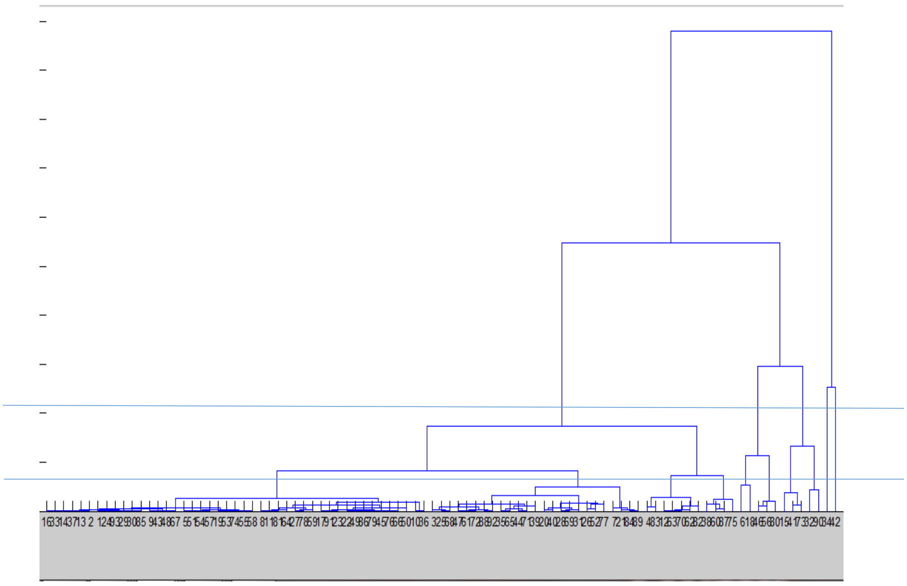

FIGURE 5.1: Dendogram for hierarchical clustering using euclidean similarity criteria

upper threshold, we have 5 clusters of countries. If we use another threshold, we have ten clusters of countries.

We clustered countries in 7 and 5 groups. The summarized dendogram for hierarchical clustering using euclidean similarity criteria for 7 groups has been shown in figure 5.2.

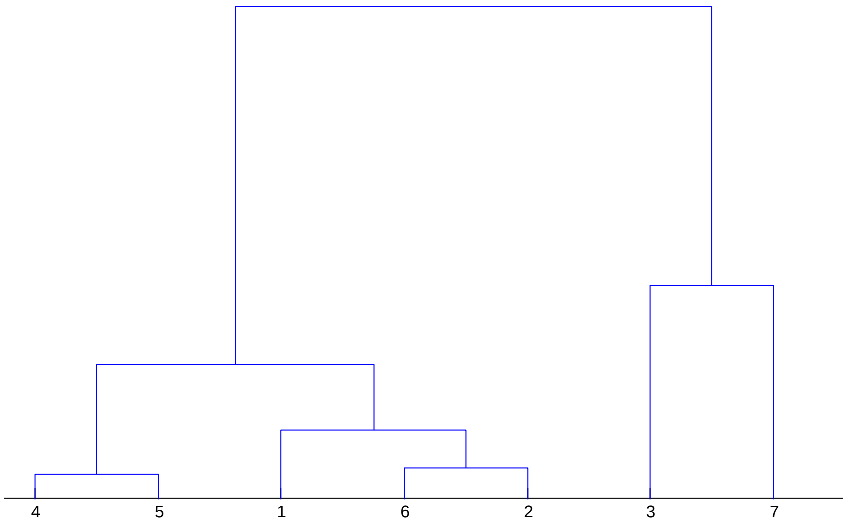

FIGURE 5.2: Dendogram for hierarchical clustering using euclidean similarity criteria for seven groups

We applied hierarchical clustering using euclidean similarity criteria to get seven clusters. Six clusters of countries have been shown in table 5.1. All other countries make the last group.

TABLE 5.1: Clusters of countries with hierarchical clustering using euclidean similarity criteria

Rank	Countries				
1	Unites States				
2	China				
3	India	Canada	France	Italy	Brazil
4	Australia	Korea,Rep	Mexico	Spain	
5	Japan				
6	Germany				

We applied hierarchical clustering using euclidean similarity criteria to get five clusters. Four clusters of countries have been shown in table 5.1. All other countries make the last group.

TABLE 5.2: Clusters of countries with hierarchical clustering using euclidean similarity criteria

Rank	Countries						
1	Unites States						
2	China						
3	Australia	Korea,Rep	Mexico	Spain	India	Canada	France
Italy	Brazil						
4	Japan	Germany					

Generally, hierarchical methods have following strengths:

- This method of clustering is versatile. There are different linkage functions and each function can be used for various purposes.
- Hierarchical methods does not make one partition. They make multiple nested partitions, which allow us to choose a partition according to the desired similarity level.

hierarchical methods have main following disadvantages:

- Clustering a large data set using a hierarchical algorithm has a huge cost.
- Hierarchical methods cannot undo what was done previously.

5.0.3 K means Clustering

K-means (MacQueen, 1967) is a famous clustering algorithm. It needs to know the number of clusters. Suppose a database with n objects is given. Partitioning method makes k partitions. Each partition will represent a cluster($k <= n$). There are some requirements for K-means clustering:

1.Each partition contains at least one object.

2.Each object belongs to only one group.

Assume we have n observations $(x_1, x_2, ..., x_n)$. The number of clusters is given (k). So there are k sets $S = (S_1, S_2, ..., S_k)$. K-means algorithm finds sets of S_k where:

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2$$

K means Algorithm can be summarized as below steps (Hamerly, G.2002):

1.k initial means are randomly generated within the data domain

2.k clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

3.The centroid of each cluster becomes the new mean.

4.Steps 2 and 3 are repeated until convergence has been reached.

Results of k-means clustering for two given number of clusters have been shown in figure 5.3 and 5.4.

In factor analysis, we showed seven countries (United States, China, India, Qatar, Iran, Lebanon, and Venezuela) as the most extreme cases in our data set. We removed those countries from the data set. Then we applied k-means clustering to our new data set. Using a data set without outliers gives us better results. The results have been shown in figure 5.5.

1	China	3	Sweden	4	Cyprus	4	Malta	4	Tunisia
2	Germany	3	Switzerland	4	Czech Republic	4	Mauritius	4	Ukraine
2	Japan	3	Thailand	4	Ecuador	4	Moldova	4	Uruguay
3	Argentina	3	United Arab Emirates	4	El Salvador	4	Montenegro	4	Vietnam
3	Austria	3	Venezuela	4	Estonia	4	Morocco	4	Zambia
3	Belgium	4	Afghanistan	4	Georgia	4	New Zealand	5	United States
3	Chile	4	Albania	4	Greece	4	Oman	6	Australia
3	Colombia	4	Algeria	4	Hungary	4	Pakistan	6	Indonesia
3	Denmark	4	Armenia	4	Iceland	4	Panama	6	Korea, Rep.
3	Egypt	4	Azerbaijan	4	Ireland	4	Paraguay	6	Mexico
3	Finland	4	Bahrain	4	Jordan	4	Peru	6	Netherlands
3	Iran, Islamic Rep.	4	Bangladesh	4	Kazakhstan	4	Portugal	6	Spain
3	Israel	4	Belarus	4	Kenya	4	Qatar	6	Turkey
3	Malaysia	4	Bosnia and Herzegovina	4	Kuwait	4	Romania	7	Brazil
3	Nigeria	4	Botswana	4	Latvia	4	Samoa	7	Canada
3	Norway	4	Brunei Darussalam	4	Lebanon	4	Serbia	7	France
3	Philippines	4	Bulgaria	4	Lithuania	4	Slovak Republic	7	India
3	Poland	4	Cape Verde	4	Luxembourg	4	Slovenia	7	Italy
3	Saudi Arabia	4	Costa Rica	4	Macedonia, FYR	4	Sri Lanka	7	Russian Federation
3	Singapore	4	Croatia	4	Maldives	4	Trinidad and Tobago	7	United Kingdom

FIGURE 5.3: 7 clusters of countries using K means

1	China	4	United Kingdom	7	Armenia	7	Malta	8	Singapore
2	Australia	5	Algeria	7	Bahrain	7	Mauritius	8	Thailand
2	Brazil	5	Czech Republic	7	Bosnia and Herzegovina	7	Moldova	9	Indonesia
2	Canada	5	Egypt	7	Botswana	7	Montenegro	9	Mexico
2	France	5	Finland	7	Brunei Darussalam	7	Panama	9	Netherlands
2	India	5	Greece	7	Bulgaria	7	Paraguay	9	Saudi Arabia
2	Italy	5	Ireland	7	Cape Verde	7	Samoa	9	Sweden
2	Korea, Rep.	5	Israel	7	Costa Rica	7	Serbia	9	Switzerland
2	Russian Federation	5	Kazakhstan	7	Cyprus	7	Slovenia	9	Turkey
2	Spain	5	Kuwait	7	El Salvador	7	Trinidad and Tobago	10	Azerbaijan
3	Argentina	5	New Zealand	7	Estonia	7	Tunisia	10	Bangladesh
3	Austria	5	Pakistan	7	Georgia	7	Uruguay	10	Belarus
3	Iran, Islamic Rep.	5	Peru	7	Iceland	7	Afghanistan	10	Croatia
3	Nigeria	5	Portugal	7	Jordan	7	Zambia	10	Ecuador
3	Norway	5	Qatar	7	Kenya	8	Belgium	10	Hungary
3	Poland	5	Romania	7	Latvia	8	Chile	10	Luxembourg
3	United Arab Emirates	5	Ukraine	7	Lebanon	8	Colombia	10	Morocco
3	Venezuela	5	Vietnam	7	Lithuania	8	Denmark	10	Oman
4	Germany	6	United States	7	Macedonia, FYR	8	Malaysia	10	Slovak Republic
4	Japan	7	Albania	7	Maldives	8	Philippines	10	Sri Lanka

FIGURE 5.4: 10 clusters of countries using K means

1	Argentina	2	Thailand	3	Iceland	3	Sri Lanka	5	Romania
1	Belgium	2	United Arab Emirates	3	Jordan	3	Trinidad and Tobago	5	Ukraine
1	Indonesia	3	Afghanistan	3	Kenya	3	Tunisia	5	Vietnam
1	Netherlan ds	3	Albania	3	Latvia	3	Uruguay	6	Brazil
1	Nigeria	3	Armenia	3	Lithuania	3	Zambia	6	France
1	Norway	3	Azerbaijan	3	Luxembourg	4	Germany	6	Italy
1	Poland	3	Bahrain	3	Macedonia, FYR	4	Japan	6	Russian Federation
1	Saudi Arabia	3	Belarus	3	Maldives	5	Algeria	6	United Kingdom
1	Sweden	3	Bosnia and Herzegovina	3	Malta	5	Bangladesh	7	Australia
1	Switzerla nd	3	Botswana	3	Mauritius	5	Czech Republic	7	Canada
1	Turkey	3	Brunei Darussalam	3	Moldova	5	Finland	7	Korea, Rep.
2	Austria	3	Bulgaria	3	Montenegro	5	Greece	7	Mexico
2	Chile	3	Cape Verde	3	Morocco	5	Hungary	7	Spain
2	Colombia	3	Costa Rica	3	Oman	5	Ireland		
2	Denmark	3	Croatia	3	Panama	5	Kazakhstan		
2	Egypt	3	Cyprus	3	Paraguay	5	Kuwait		
2	Israel	3	Ecuador	3	Samoa	5	New Zealand		
2	Malaysia	3	El Salvador	3	Serbia	5	Pakistan		
2	Philippine s	3	Estonia	3	Slovak Republic	5	Peru		
2	Singapore	3	Georgia	3	Slovenia	5	Portugal		

FIGURE 5.5: 7 clusters of countries using K means after removing outliers

Chapter 6

Conclusion

6.1 Discussion

In this research, factors affecting global site selection has been collected from the literature. Collection of such a diverse and comprehensive list of attributes for the problem of global facility location is an important outcome of this research. Although collected factors for different firms have different levels of significance, approximately all the collected attributes impact the decisions of manufacturing site selection. In addition to these primary factors, there are categories of secondary factors that can be added to the analysis. Factors not only have different levels of significance for different industries, but also there are some other specific factors for each industry. For instance the proximity of suppliers and market to the facility location, or the price of raw material required for the industry in each country are secondary factors. In addition to various industries, depending on the companies strategies weighting of factors are different. Therefore in this research we skipped weighting of factors, while it could have significant effects on our results. Taking advantage of the flexibility of clustering, the decision makers can first find the appropriate pool of countries and then, they can add the secondary factors for these countries for further customization of the solution to their specific requirements. A suggested procedure to find the best country or countries to locate facilities described in the flowchart in figure 6.1.

Factor analysis gave us important insights about relations between factors, their uniqueness, redundancies, and duplications. After applying factor analysis, we reduced number of factors. We should point out that the solution for factor analysis is not unique.

The aim of this research is not presenting the best solution of global site selection. This problem is very general. In order to find the best solution, the problem needs many specifications. And the results may vary for each firm. For example, weighting depending on firms priorities can make different clustering results. The goal of this research was presenting a frame work for global site selection.

6.2 Conclusion

This research presents a flexible and quantitative approach to manufacturing facility location problem. The manufacturing site selection factors are quantified using existing real world data. Then two main types of cluster analyses are employed to identify suitable manufacturing locations based on a wide range of economic, social, political, and environmental factors. The clusters of countries demonstrate the group of countries with similar

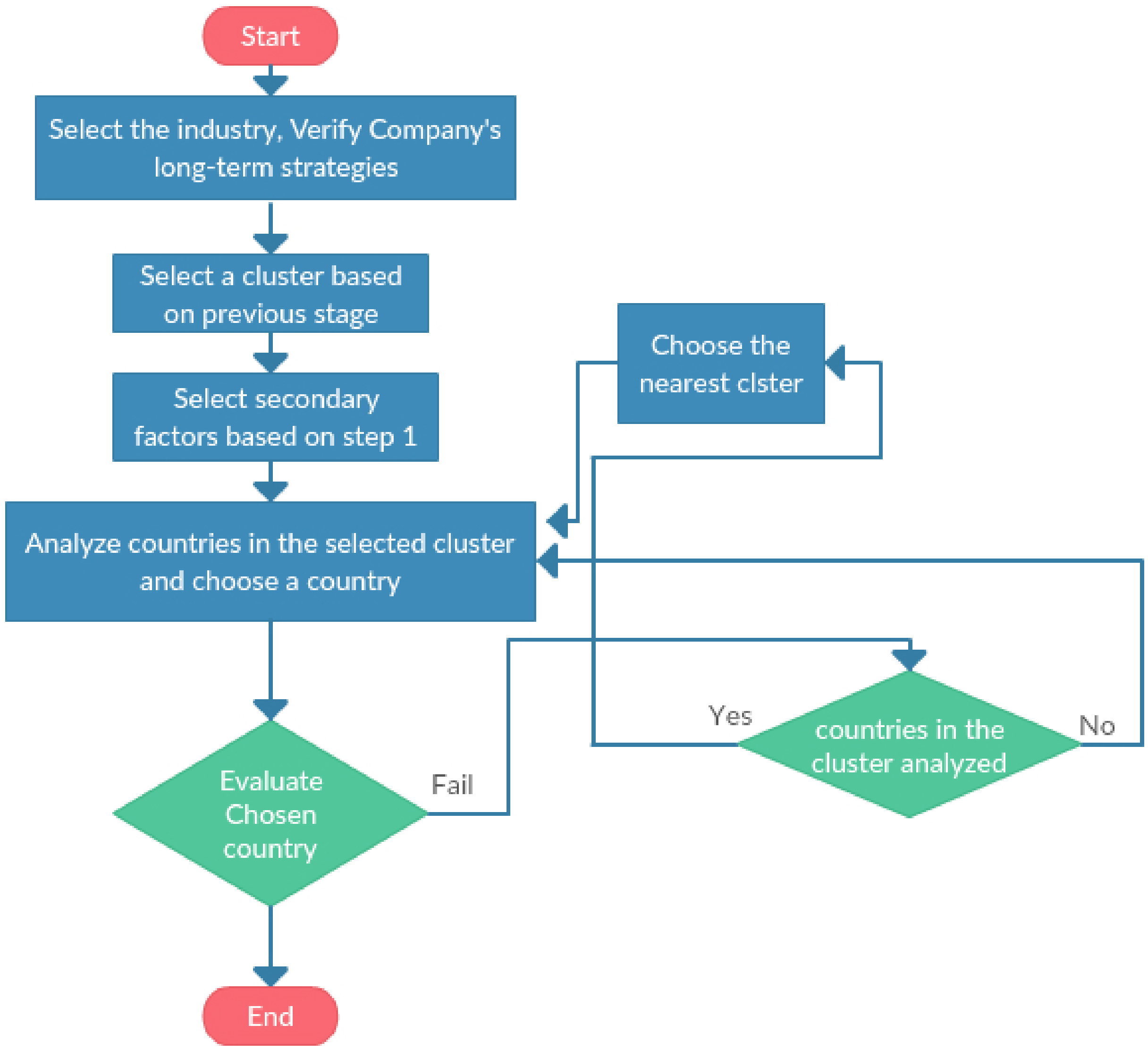

FIGURE 6.1: Decision Making Algorithm

potentials for manufacturing facility locations. This approach provides a framework which facilitates the decision making regarding manufacturing facility location selection.

Chapter 7

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