

# AN ANALYSIS OF DECISION MAKERS' PREFERENCES THROUGH SUPPLIER SELECTION PROBLEM

# SİNEM TAŞBAŞI

Master's Thesis

Graduate School

İzmir University of Economic

İzmir

2021

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A Thesis Submitted to

The Graduate School of Izmir University of Economics

Master Program in Logistics Management

İzmir

2021

#### ABSTRACT

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Taşbaşı, Sinem

Master Program in Logistics Management

Advisor: Assoc. Prof. Dr. Muhittin Hakan Demir

Co-advisor: Assoc. Prof. Dr. Özgür Özpeynirci

September, 2021

In this thesis, we consider the supplier selection problem with a focus on the methods proposed. We also consider the supplier selection criteria used in different methods. Reviewed methods are all based on the compensatory approaches, where a good score of a supplier in one criterion may compensate for the poor score in another criterion. We are not aware of any non-compensatory approach proposed for the supplier selection problem. In this study, the main research question is to analyze the possibility of expressing the preferences of a decision-maker using a compensatory method for the supplier selection problem. We prepare a survey based on pairwise comparisons of specially designed suppliers evaluated on three criteria. The survey study presents the pairwise comparison questions one by one to the participant and the responses of the participant affect the next question asked. For each participant of the survey, we check the consistency of the responses using two different mixed integer programming models; the former model assumes the supplier selection method is a compensatory method based on a linear value function, and the latter assumes the use of MR-Sort, a noncompensatory method. The survey results indicate that a linear value function can explain 22% of the participants' preferences, whereas MR-Sort is capable of explaining the preferences of all participants.

Keywords: Supplier Selection, Decision Making, Compensatory Approach, Non-Compensatory Approach, Survey Study, Mathematical Modeling.

### ÖZET

# KARAR VERİCİLERİN TERCİHLERİNİN TEDARİKÇİ SEÇİM PROBLEMİ İLE ANALİZİ

Taşbaşı, Sinem

Lojistik Yönetimi Yüksek Lisans Programı

Tez Danışmanı: Doç. Dr. Muhittin Hakan Demir

İkinci Tez Danışmanı: Doç. Dr. Özgür Özpeynirci

#### Eylül, 2021

Bu tezde, önerilen yöntemlere odaklanarak tedarikçi seçim problemini ele alıyoruz. Farklı yöntemlerde kullanılan tedarikçi seçim kriterlerini de dikkate alıyoruz. İncelenen yöntemlerin tümü, bir tedarikçinin bir kriterdeki iyi puanının başka bir kriterdeki düşük puanı telafi edebileceği telafi edici yaklaşımlara dayanmaktadır. Tedarikçi seçimi problemi için önerilen herhangi bir telafi edici olmayan yaklaşımın farkında değiliz. Bu çalışmada ana araştırma sorusu, tedarikçi seçim problemi için telafi edici bir yöntem kullanarak bir karar vericinin tercihlerini ifade etme olasılığını analiz etmektir. Özel olarak tasarlanmış, tedarikçilerin üç kritere göre değerlendirildiği ikili karşılaştırmalara dayalı bir anket hazırlıyoruz. Anket, ikili karşılaştırma sorularını tek tek katılımcıya sunar ve katılımcının yanıtları bir sonraki sorulacak soruyu etkiler. Anketin her katılımcısı için, iki farklı karma tamsayı programlama modeli kullanarak yanıtların tutarlılığını kontrol ediyoruz; ilk model, tedarikçi seçim yönteminin doğrusal bir değer fonksiyonuna dayalı telafi edici bir yöntem olduğunu varsayar ve ikincisi, telafi edici olmayan bir yöntem olan MR-Sort'un kullanıldığını varsayar. Anket sonuçları, ağırlıklı toplam fayda fonksiyonunun katılımcıların tercihlerinin %22'sini açıklayabildiğini, oysa MR-Sort'un tüm katılımcıların tercihlerini açıklayabildiğini göstermektedir.

Anahtar Kelimeler: Tedarikçi Seçimi, Karar Verme, Telafi Edici Yaklaşım, Telafi Edici Olmayan Yaklaşım, Anket Çalışması, Matematiksel Modelleme.

This thesis is dedicated to dear Doğan Gök, who has always been by my side and has always trusted and encouraged me. Without you, this thesis would not have been possible.



#### ACKNOWLEDGMENTS

I would like to express my deep and sincere gratitude to my advisor Assoc. Prof. Dr. Muhittin Hakan Demir, and my co-advisor Assoc. Prof. Dr. Özgür Özpeynirci for the support to this study and research, for their patience, and immense knowledge. Their guidance has been of great help to me in researching and writing this thesis. I am very lucky to have two such valuable advisors. I would also like to express my sincere gratitude to Lecturer Dr. Sinem Tokçaer, and Res. Asst. Burçin Özdamar for their unconditional support and guidance. I will always keep in mind all your support, care, and patience. Finally, I would like to express my endless thanks to my beloved family, my dear friends Nurgül Turan and Kawtar Hida, who have always supported me.

#### PREFACE

In this thesis, the main research question is to analyze the possibility of expressing the preferences of a decision-maker using a compensatory method for the supplier selection problem. We wrote to meet the graduation requirements of the Izmir University of Economics, Department of Logistics Management, masters with thesis. We prepared it in 2 semesters in total between 2020 and 2021.

I am very lucky to have the opportunity to work on the current study with Assoc. Prof. Dr. Özgür Özpeynirci from the determination of the subject until the completion of the thesis. Özpeynirci is a unique lecturer with his discipline and love for his profession. Throughout the research, we exchanged on a weekly basis with my co-advisor, Assoc. Prof. Dr. Özgür Özpeynirci. The process of writing the thesis was a great pleasure thanks to my co-advisors patience, pertinent recommendations, and support.

The thesis writing process is a long process that requires a consistent tempo. I recommend people planning to prepare a research work to choose wisely their advisor or advisors, with whom they would build a great rapport to help them out in completing their study successfully. It is a great advantage to collaborate with an advisor or advisors you enjoy working with on a subject that matters to the researcher. I was very lucky in this regard because I had the opportunity to bring the current research to a successful conclusion with my advisor's guidance.

# IZMIR 08/09/2021

Sinem Taşbaşı

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#### LIST OF ABBREVIATIONS

AD : Axiomatic Architecture

AHP : Analytical Hierarchy Process

AI : Artificial Intelligence

ANOVA : Analysis of Variance

ANP : Analytical Network Processing

DEA : Data Envelopment Analysis

DEMATEL : Decision Making Trial and Evaluation Laboratory

DM : Decision-Maker

DMAI : Data Mining and Artificial Intelligence

**GP** : Goal Programming

HFPR : Human Resource Planning

ILP : Integer Linear Programming

ISM : Interpretive Structural Model

JIT : Just-In-Time

LP : Linear Programming

MCDM : Multi-Criteria Decision-Making

MILP : Mixed-Integer Programming

MP : Mathematical Programming

MR-SORT : Majority Rule Sorting

PCA : Principal Component Analysis

PHFLTS : Proportional Hesitant Fuzzy Linguistic Term Set

SEM : Structural Equation Modelling

**QFD** : Quality Function Deployment

#### **CHAPTER 1: INTRODUCTION**

Supplier selection is a process in which a set of alternative suppliers are considered and contracts are made with some of these alternative suppliers as a result of the identification, evaluation, and certain analysis of the alternative suppliers (Chai, and Ngai, 2020). The supplier selection process is a purchasing decision problem that aims to increase the competitiveness of the companies (Aouadni, Aouadni, and Rebaï, 2019). Working with the right suppliers gives companies a great competitive advantage. For this reason, the supplier selection problem has received great attention in the literature and a large number of studies are available in this field.

While examining the supplier selection methods and criteria used in the literature, we realize that hundreds of methods and criteria are used in this field. Therefore, we examine which methods and criteria are commonly used in the supplier selection problem with this thesis. Our aim here is to reveal the commonly used supplier selection methods and criteria. Our research in this area is under two separate headings in Chapter 2: Literature Review; (i) Supplier Selection Methods and (ii) Supplier Selection Criteria.

While examining the supplier selection methods, we realize that the methods used are compensatory. A compensatory method allows a supplier's high score in one criterion to compensate for its medium or low score in another criterion. On the other hand, a non-compensatory method does not allow this high score to compensate for another criterion. To the best of our knowledge, there is no study on the supplier selection problem that discusses the use of a non-compensatory method or why a noncompensatory method is valuable. Based on this gap in the literature, we claim that a decision-maker (DM) can make evaluations in a non-compensatory method in supplier selection in real life. To prove this claim, we prepare an online anonymous survey study to be conducted by DMs that are professionals involved with the supplier selection. We prepare a survey based on pairwise comparisons in which specially designed suppliers are evaluated according to three criteria. The survey presents the pairwise comparison questions one by one to the participant and the responses of the participant affect the next question asked. In this way, we aim to understand the supplier selection method in the minds of DMs. As a result of our survey study, the preferences of only 12 of 55 survey participants can be explained by the linear value function, which is a compensatory method. In other words, no inconsistency is found in the answers given by these 12 survey participants to the survey questions. However, the preferences of the remaining 43 participants are not explained by the value function, which is a compensatory method. This situation shows us that there is a need for non-compensatory methods in the literature.

We examine whether we can explain the preferences of these DMs, which cannot be explained by the linear value function, which is a compensatory method, with the MR-Sort method, which is a non-compensatory method. In addition, to support our study of supplier selection criteria, which we discuss in the literature review section, we question the 3 most important supplier selection criteria according to the survey participants.

In this study, the main research question is to analyze the possibility of expressing the preferences of a DM using a compensatory method for the supplier selection problem. The following is the structure of this thesis: In Chapter 2, we present a literature review of supplier selection methods and criteria. In Chapter 3, we discuss the methodology used and describe the mathematical models applied. In Chapter 4, we describe the design of the online anonymous survey. In Chapter 5, we analyze the responses to the online anonymous survey. In Section 6, we conclude our study.

#### **CHAPTER 2: LITERATURE REVIEW**

Beil (2010) defines supplier selection as a process where the buyer selects, evaluates, and contracts with suppliers. The process starts with the identification of potential suppliers. The DM then asks for various information about themselves to evaluate these suppliers. In this information exchange process, suppliers prepare a proposal in terms of contract terms such as price, delivery time, cost according to demand. The terms of the contract usually become clear during the negotiation process. Finally, the DM determines which supplier(s) to work with and then tracks the supplier throughout the term of the contract to support future supplier selection iterations (Beil, 2010). These steps provide a general overview of the supplier selection process and each step is a long and detailed issue that must be completed with care.

The supplier selection problem is a purchasing decision problem aiming to increase the competitiveness of the company. It includes various methods to analyze the performance of suppliers and the various models used within these methods (Aouadni, Aouadni, and Rebaï, 2019). Two commonly defined problem types are as follows(Xia, and Wu, 2007); (i) the first one is the selection of a single supplier. One supplier must meet all buyer demands and managers only need to pick one supplier from the set of potential suppliers. (ii) The second one is multi-source supplier selection. In this problem, a single supplier cannot meet all needs of the buyer and it is the choice that forces the buyer to purchase the same or different pieces from more than one supplier. This decision-making process is complex because the evaluation and decision-making process is determined by a variety of quantitative and qualitative criteria. In a situation where qualitative and quantitative criteria are used together, a set of decision-making methods are recommended in the literature to overcome this complexity (Aouadni, Aouadni, and Rebaï, 2019).

There are various scenarios in the supplier selection process. For example, you can work with a single supplier for each piece or you can work with multiple suppliers for a one-piece. Also, when it comes to ordering five different pieces at the same time, you can work with different suppliers for these five pieces. It is possible to select various combinations during the supplier selection process. Working with a single supplier has some advantages and disadvantages. When you work with a single reliable supplier, that supplier can give you a competitive advantage. For example, it can assist you in your design and manufacturing decisions by collaborating with you throughout the product development process to improve quality and productivity. On the one hand, when this supplier faces a financial crisis, the difficult situation of the company affects you deeply. For instance, if the supplier unexpectedly goes bankrupt, the time it takes to reach an agreement with a new supplier can become a big problem for your company. Therefore, it is important to decide how many parts you are working on and whether to produce those parts with a single supplier or with multiple suppliers for the supplier selection process (Han, Wilson, and Dant, 1993).

Two key issues to consider on the supplier selection problem are supplier selection methods and supplier selection criteria. Therefore, while examining the literature, we discussed these two issues under two separate headings. In this section, we discuss supplier selection methods and criteria used during the selection process.

#### 2.1 Methods for Supplier Selection

Working with the right suppliers provides not only a strategic advantage but also a cost-cutting and quality-improvement advantage (Degraeve, and Roodhooft, 1999). Therefore, the supplier selection problem is a subject that both academics and DMs are interested in. There are numerous studies on the supplier selection problem in the literature. These studies propose several methods while addressing the supplier selection problem.

Supplier selection problem is generally a process in which multi-criteria decisionmaking (MCDM) approaches are used (Mafakheri et al., 2011). When we examine the supplier selection problem in the literature, we realize that MCDM approaches are widely used for solving this problem. MCDM approaches aim to help DMs solve challenges that require a complex decision-making process. These approaches help DMs to solve the problem of supplier selection in cases where there are multiple conflicting criteria (Ho, 2008). There are hundreds of different methods within the MCDM approaches. It is possible to discuss these methods under two headings; individual methods and integrated methods. An approach is considered as an individual method if it uses a single method on the supplier selection problem. On the other hand, an approach is said to be an integrated method if it uses multiple methods to deal with the supplier selection problem (Ho, Xu, and Dey, 2010). Individual methods are frequently preferred in the supplier selection problem due to their ease of use. However, individual methods may not be sufficient to predict some unknown points. For example, there are various unknown points in the supplier selection problem, such as insufficient financing, quality problems, inadequate delivery, logistics capabilities, and technological capabilities. Using an individual method in the supplier selection problem may not be sufficient to predict these points. It may produce erroneous conclusions. On the other hand, integrated methods are better at estimating unknown points, because they produce more reliable results. Two or more methods used in the supplier selection problem are always more powerful in estimating unknown points. However, individual methods for supplier selection problems have been used more widely in the literature than integrated methods, due to their ease of use (Büyüközkan, 2012).

There are hundreds of different methods used in the supplier selection problem. There are so many studies on this field in the literature. We review over 40 scientific journal articles to find the most widely used supplier selection methods in the literature. To this end, below we discuss most of these journal articles using MCDM approaches for supplier selection and criteria. The reader needs to pay attention to the dates of the research while examining the literature reviews in this field. The methods and solution strategies used vary over the years. For this reason, we have compiled the methods and changes applied in this field in the last 15 years to present to you.

The analytical hierarchy process (AHP) is a common MCDM approach introduced by Thomas L. Saaty in 1980. It is used to rank potential suppliers hierarchically. The AHP method is widely used due to its wide applicability, ease of use, and flexibility. Ho (2008) claims that the integrated AHP method can create a more reliable and successful decision method than individual AHP. They analyze the literature of integrated AHP applications published between 1997 and 2006. As a result of the 66 journal articles they review, some AHP-integrated tools have emerged due to their prominence, broad applicability, and efficiency in decision-making. These are, in order of popularity, mathematical programming (MP), quality function deployment (QFD), meta-heuristics, SWOT analysis, and data envelopment analysis (DEA). These are the most popular methods used with AHP in the literature review conducted between those years. They also find that MP, which they find to be the most popular method, is divided by four among themselves. These are linear programming (LP), integer linear programming (ILP), mixed-integer linear programming (MILP), and goal programming (GP). Among these methods, integrated AHP-GP and AHP-QFD are the most used integrated methods. The most prominent main explanation of the combination of the AHP-GP method is that individual strategies have certain benefits.

"Good decisions are based on consistent judgments most often" Badri, and Abdulla (2004)

point out. AHP method serves as feedback. It helps DMs to revise and update their decisions to avoid uncertainty. As a result, it is ensured that the decisions made are consistent so that it is an essential component of making good decisions. The performance of the AHP, however, is merely the relative value weightings of the parameters and attributes. In addition to the weightings of alternate sites, DMs often need to consider the resource restrictions in certain MCDM problems (Badri, 1999). Therefore, AHP can be compensated by the GP method. Based on the above analysis, Ho (2008) believes that bringing AHP and GP together benefits the decision-making process. The reason why integrated AHP and QFD is another most popular method among mathematical methods is explained as follows. The essential ratings of company requirements are usually randomly decided by the DMs. There may be some inconsistency as a result of this. AHP is used to measure the relative value weight of customer requirements in order to solve this situation. This is the main reason why the integrated AHP-QFD method has been widely implemented (Ho, 2008).

Ho, Xu, and Dey (2010) review 78 journal articles published between 2000 and 2008 on the supplier evaluation and selection problem. They find that individual methods are used more widely than integrated methods with this review. They find that DEA, MP, AHP, case-based reasoning, analytical network processing (ANP), fuzzy set theory, SMART, and genetic algorithms are the most commonly used individual methods. Besides, they find that AHP and GP are the most common integrated methods, as Ho also states earlier in their 2008 article. According to both articles, it is thought that combining AHP and GP methods are more beneficial for the decision-making process. Agarwal et al. (2011) also review the literature on supplier selection methods. The data they obtained and their sorting methods turned out to be the same as those obtained in the articles above.

Büyüközkan (2012) proposes a decision method for supplier performance evaluation, taking into account different environmental performance parameters. In this proposed method, a fuzzy AHP is applied to evaluate the relative weights of the evaluation parameters. Then, the Axiomatic architecture (AD)-based fuzzy group decision-making method is applied to rank green suppliers. According to Büyüközkan (2012), the AHP method is the most popular in the MCDM approach. On the other hand, AHP is often matched due to its inability to cope with decision-making problems in uncertain situations. It is considered to be poor in addressing the ambiguity of concepts regarding people's subjective judgments. In other words, people cannot act completely rationally while making various decisions. Fuzzy AHP enables this decision-making process to be defined more accurately. For this reason, Büyüközkan (2012) uses AHP and AD methods in fuzzy environments to solve this problem.

Emrouznejad, and Marra (2017) discuss individual and integrated AHP methods from 1979 to 2017 from a historical perspective. They examine this historical process in three periods: 1979–1990, 1991–2001, and 2002–2017. The purpose is to identify research that played an important role in the growth of AHP and determine the places where it is implemented. The first period (1979-1990) has a smaller number of disciplines in which AHP is used than the other periods. In this first period, the use of the AHP method is limited. During this period, the authors who propose the first formulation of the AHP are Saaty, Vargas, Harker, and their co-authors. These authors propose the theoretical foundations of the AHP method. In the second period (1991-2001), there is an increase in the use of the AHP method. AHP methods began to be used in various fields such as mathematical methods, computer science, business, and management studies. In the third period (2002-2017), the increasing interest in the AHP method is at its highest level. There are two dominant methods most used in this period. These are the fuzzy-based method and AHP; and the socalled integrated AHP. In conjunction with other MCDM approaches, there have been discussions of information regarding the more advanced methods proposed for

improving AHP. Researchers propose AHP in response to a need for innovative approaches to solving complex decision-making problems. This article is the first review to address AHP in terms of both methodological development and its applications. It explores, using social network analysis and scientometrics, the pattern of growth of the AHP research area, and describes its conceptual framework (Emrouznejad, and Marra, 2017).

Ho, and Ma (2018) conduct a study of the literature published between 2007 and 2016 on the integrated AHP method and implementations. They compare these studies with articles from 1997-2006 published in the previous decade. This article is also a follow-up study for Ho (2008). In their literature study, AHP is integrated with a single method in 52 of the 88 journals they review. In the remaining 36 journals, AHP is integrated with more than two methods. In other words, AHP has been combined with three or more methods in the supplier selection problem. As a result, Ho, and Ma (2018) find that integrated AHP and fuzzy set theory methods are widely used during these years. The reason these methods are common is that it allows DMs to consider uncertainty. In such a case, DMs have the opportunity to cooperate with the right suppliers. They find that after the integrated AHP and fuzzy set theory methods, the following methods are most commonly used, respectively, integrated AHP and Simulation, integrated AHP and OHP and OFD, integrated AHP and simulation, integrated AHP and other methods, and finally integrated AHP and multiple methods (Ho, and Ma, 2018).

DEA is another widely applied method in decision-making. Input and output weights are needed to evaluate organizations (Izadikhah et al., 2014). This need is eliminated with the DEA method, because DEA is a systematic approach that eliminates the need for weight determination of DMs (Charnes et al., 1978). DEA is a method that can be used in many different areas such as benchmarking, goal setting, measuring returns to scale, and measuring congestion (Emrouznejad, and Yang, 2018). Izadikhah, and Saen (2020) focus on sustainable supplier selection in a MCDM problem. They mention in their article that the use of DEA is one of the significant ways to evaluate sustainable suppliers. There are various DEA methods, it may not provide sufficient efficiency in ranking suppliers. Izadikhah, and Saen (2020) find

seven different methods to rank these suppliers. These seven methods, respectively, cross-efficiency methods, methods based on finding optimal weights, superefficiency methods, benchmarking methods, using statistical tools for ranking suppliers, a combination of MCDM and DEA methods, and ranking inefficient suppliers. All these methods have some disadvantages such as the emergence of alternative solutions, the feasibility of suppliers and the inadequacy of sequencing, and the inability to create a good supplier ranking. For this reason, Izadikhah, and Saen (2020) propose a new DEA method called context-dependent DEA for ranking suppliers. This method proposed by Izadikhah, and Saen (2020) is helpful to explain whether a supplier can gradually improve its efficiency limit. For each efficiency limit, this method determines the right weights. Izadikhan, and Saen (2020) evaluate the sustainability of 14 hydraulic tank suppliers to show that context-dependent DEA works. They compare their results with the AP method. The proposed method is able to rank all its efficient and inefficient suppliers.

Song et al. (2017) suggest a prospect theory-based selection method for solving the real-world problem of environmentally sustainable supplier selection. Kahneman and Tversky first introduced prospect theory in 1979. It is a behavioral method that shows how DMs make decisions when they are caught between alternatives that include risk and uncertainty (Kahneman, and Tversky, 1979). Song et al. (2017) take into account the producer's psychological and behavioral factors in supplier selection. As an example, they take an integrated circuit manufacturer company in Shenzhen, China. The company wants to select an electronic product provider to meet their demands for a certain number of parts. At the same time, they want this chosen supplier to be an environmentally friendly company. For this purpose, they create supplier selection indices for producers. The attribute is then analyzed as a measure for producer standards, according to the research. The payoff and loss matrices were then compared to the expectation reference point, resulting in a payoff matrix and loss matrix. Eventually, the study applied prospect theory to determine the detailed prospect value of each provider. As a result, the method met certain requirements regarding the practical implementation of the decision process and the calculated results turned out to be correct. In real life, DMs focus on gains and losses while making their decisions. Prospect theory describes the behavior of the DM towards gains and losses. It also significantly reduces computational complexity by using the programming language (Song et al., 2017).

QFD is a powerful method that helps design and develop products and services (Karsak, 2004; Ji et al., 2014). It is a form of product planning that is guided by the needs of the consumer. Its goal is to identify potential consumers' needs. (Mehrjerdi, 2010). QFD has several advantages as it strengthens communication between customers and technicians. These are various advantages such as shortening the product development cycle time, reducing engineering costs, and increasing the performance of the production process (Carnevalli, and Miguel, 2008). On the other hand, traditional QFD has a few weaknesses that reduce its performance and potential implementations. These are reasons such as experts having to present their opinions using exact values, incorrect ordering of engineering features, and using a linear summation method that does not take into account the choice behavior of DMs (Huang et al., 2019). They propose a new QFD method using proportional hesitant fuzzy linguistic term sets (PHFLTSs) and prospect theory to overcome these disadvantages of traditional QFD. They work on two examples to reveal the applicability and advantages of this method. They compare the results of this study with other available QFD methods. As a result, this proposed new QFD method achieved more reasonable and reliable results.

Fallahpour et al. (2017) state that AHP-based methods are commonly used in supplier selection problems due to their ease of use, but these methods cannot get a healthy result in an uncertain and complex environment. They propose a hybrid method for sustainable supplier selection problems in complex and uncertain environments. In this article, they develop a new Hybrid method with an integrated method combining AHP and fuzzy methods. Fallahpour et al. (2017) handle an Iranian textile company as a case study. They apply the FTOPSIS methods for the supplier selection problem. The FTOPSIS method easily distinguishes the situations where the benefit is high and the cost is low and produces the most ideal solutions. FTOPSIS also allows managers to include uncertainty and the computation process doesn't take much time (Fallahpour et al., 2017). With this method they develop, they are able to cope with inconsistency, uncertainty, and computational complexity.

Govindan et al. (2015) review the literature on supplier evaluation and selection published between 1997 and 2011. They notice that there is a large literature in these areas but less literature on a green supplier evaluation that takes environmental factors into account. Therefore, they review articles on green supply selection published in international scientific journals and conference proceedings. As a result of their research, they realize that most of the literature uses a single fuzzy-based method to solve the supplier selection problem. They believe this may be due to the ease of using a single method on the problem and their desire to limit the complexity of the methods. However, Govindan et al. (2015) believe that integrated methods achieve more reliable results in the real world. As another result of the research, they find that the most popular supplier selection methods are AHP, ANP, and DEA, respectively. Although the use of the AHP method is widespread, the number of researchers criticizing this method is quite high. Therefore, Govindan et al. (2015) argue that when implementing AHP, attention should be paid to its limitations.

Chai, Liu, and Ngai (2013) conduct a literature search on 123 journal articles published from 2008 to 2012 for supplier selection. They use a four-part methodological decision analysis: decision problems, decision-makers, decision contexts, and decision approaches. Among the articles they examine, they discuss 26 decision-making methods under three headings in total. These are MCDM methods, MP, and artificial intelligence (AI) methods. Each of the 26 techniques is evaluated by Chai, Liu, and Ngai (2013), and methods of integrating these techniques for supplier selection are analyzed. The most used integrated methods are AHP, ANP, DEA, respectively (Chai, Liu, and Ngai, 2013). This study by Chai, Liu, and Ngai (2013) is still an effective and important literature study.

Chai, and Ngai publish an article in 2020 on decision-making methods for supplier selection. They attract attention to state-of-the-art developments in decision-making techniques with this new article. At the same time, they discuss various topics that support future research in this article. These are risk and uncertainty, economic theories, stock bases, rating methods, preference of green and strategic supplies, and party and negotiating problems. Based on the literature they have compiled, these topics are the main observations in this article (Chai, and Ngai, 2020). Chai, and Ngai (2020) review major supplier selection literature over the past five years. The

works of literature they review provide insight into the future development of supplier selection but none of them have caught up with the transitions in the latest technology development. Therefore, Chai and Ngai examine methods involving these latest technological advances with this article. They discuss techniques in these three categories: MCDM, MP, and data mining, and artificial intelligence methods (DMAI). Beyond these, they also discuss the emerging techniques at the same time. They find that the two methods are used very often in supplier selection. The first is the method by which needs are directly determined using mathematical programming. The second method is models using a hybrid decision process or a combination of decision methods. This study profits from other disciplines such as computing, data, and economics. Chai, and Ngai (2020) provide valuable insight into their current work on supplier selection with this article.

Zimmer, Fröhling, and Schultmann (2016) conduct a review of the scientific literature on sustainable supplier management, focusing on methods that aid decision-making in sustainable supplier selection, monitoring, and improvement. They examined a total of 143 articles between 1997 and 2014. In the articles they review, they find that the most used methods are Fuzzy Logic, AHP, and ANP. They believe that the reason why the fuzzy logic method is popular is that it can be combined well with mathematical analytical methods and that it can handle the linguistic judgments of experts and transfer them with crisp numbers. Similarly, AHP and ANP have demonstrated their ability to regard subjective views as well as their ability to be combined with other techniques that typically deal with objective data. There are few models that suggest the formulation of criteria or development activities. Therefore, they claim that the Delphi method is useful in supporting this decision situation. They suggest that future studies should look into the Delphi method in the context of the formulation of development activities. They claim that unlike classical suppliers selection reviews such as Chai, Liu, and Ngai (2013) and Ho, Xu, and Dey (2010) methods such as ELECTRE, SMART, or nonlinear modeling have not been adequately researched in sustainable supplier management. For this reason, as a second recommendation, they recommend that future researchers work on this gap (Zimmer, Fröhling, and Schultmann, 2016).

Alikhani, Torabi, and Altay (2019) handle sustainability and risk factors in supplier selection with this article. Awasthi (2018) and Vahidi (2018) have previously discussed these two factors independently. However, as far as is known, Alikhani, Torabi, and Altay (2019) are the first researchers to deal with risk and sustainability in an interrelated way with this article. They claim that the traditional DEA approach is ineffective at distinguishing between potential suppliers due to the difficulty of the decision-making process. Therefore, they propose a multi-method approach that focuses on analytical modeling and quantitative empirical research to deal with this uncertainty. To measure the inputs of DMs, they use interval type-2 fuzzy sets and suggest an expanded super-efficiency DEA method that involves both positive and negative inputs and outputs to evaluate suppliers. They include both sustainability and suppliers' risk factors in the supplier selection problem with this method they suggest. This method has a risk-averse attitude and provides a holistic approach for DMs. Alikhani, Torabi, and Altay (2019) work on a real case to prove the effectiveness and work of this proposed method. As a result, they concluded that addressing sustainability criteria and risk factors separately led to unhealthy decisions. The AHP method is the most used MCDM approach in the literature. Mathematical methods are used after AHP to deal with risk. Fuzzy programming is also a common method for dealing with uncertainty. Other methods used to deal with uncertainty are, respectively, stochastic programming, grey theory, bootstrapping, chance-constrained DEA, Monte Carlo simulation. In recent years, DEA has become a popular decision-making method for dealing with uncertainty. This is because the DEA method can work without the need for intuitive judgment of decision-makers (Alikhani, Torabi, and Altay, 2019).

Zhang, Li, and Wang (2020) present a literature review on reverse logistics supplier selection published between 2008 and 2020. They examined supplier evaluation methods under five headings in total. These are MCDM, AI, MP, and hybrid approaches. They found that AHP and Fuzzy AHP are the most used methods among the 23 MCDM methods they examine in total. Zhang, Li, and Wang (2020) propose a three-step decision-making framework for understanding reverse logistics supplier selection. These are the establishment of selection criteria, calculation of relative weights and ranking of selection criteria, and ranking of suppliers. First, selection criteria are established by determining alternative suppliers, defining selection

criteria for supplier selection, and structuring the decision hierarchy. Second, relative weight calculation and ranking of selection criteria are calculated by determining and prioritizing the weights of criteria and sub-criteria. The Final ranking of alternative suppliers is determined by evaluating alternative suppliers, determining the final ranks of alternatives, and selecting the best suppliers (Zhang, Li, and Wang, 2020). This decision-making framework is designed for reverse logistics supplier selection, but it is also important for the supplier selection problem.

Xiong, Dong, and Wang (2020) emphasize choosing the most suitable suppliers using a multiplicative two-step human resource planning (HFPR) model. DMs take into account the results calculated by this method and can choose without deleting or adding unnecessary information. Moreover, this method allows experts to express their evaluations in a richer and more flexible language. It develops a fuzzy and uncertain environment expressed in a logically organized subset. Thus, DMs can reflect uncertainties in the final ranking. In comparison to other methods, they add a new factor level for a more detailed assessment, which can make progress systematic and objective (Xiong, Dong, and Wang, 2020).

Based on the studies of literature we have examine, we realize that there are too many methods used in the supplier selection problem. In the early years of working on the supplier selection problem, individual methods are frequently used because of their ease of use. We can see that these individual methods are still applied with a serious decrease in their use. However, individual methods are often criticized for not being good at predicting unknown points. When we look at the literature published on the supplier selection problem in the last decade, we see that integrated methods are frequently used. Integrated methods used on the supplier selection problem contribute to predicting unknown points and making healthier decisions. Each company's purchasing decisions and needs are special. Therefore, when working on the supplier problem, it is important to bring together the methods that provide the best benefit for your company. In this section, we make a limited review over the years to observe which methods are used in the supplier selection problem and the periodic changes of these methods.

#### 2.2 Criteria for Supplier Selection

In general, there are three basic stages to consider in the supplier selection process. The process starts with the identification and selection of criteria. These selected criteria may differ for each company. Then, it is continued by determining the supplier selection method according to the criteria. Finally, it ends with the selection of the supplier according to the evaluation result. In other words, a result is reached with the supplier selection method in line with certain criteria. With this result, the DM decides which suppliers to work with (Ristono, Santoso, and Tama, 2018).

Most of the literature articles on supplier selection concentrate on determining supplier evaluation methods. There is little literature on the identification and selection of criteria. However, the identification and selection of the criteria are as important as determining the supplier evaluation methods. Ristono, Santoso, and Tama (2018) handle the identification and selection of criteria based on this gap in the literature. They examine the advantages and disadvantages of the existing supplier selection criteria methods and propose a new method. By examining 34 international journal articles published between 2008 and 2018, they find four methods for selecting criteria. These are, respectively, AHP, interpretive structural model (ISM), decision-making trial and evaluation laboratory (DEMATEL), principal component analysis (PCA), and analysis of variance (ANOVA). They examine the seventeen methods used in criteria selection under four headings in total, namely: Delphi, statistical, MCDM, and mixed methods. Ristono, Santoso, and Tama (2018) find some disadvantages of the Delphi method. First, Delphi depends heavily on the panelists' expertise. In this method, it is necessary to bring together experts in the fields that are needed to get the right result. Bringing these experts together is a tough process. Furthermore, combining the perspectives of all of these experts is challenging. The second disadvantage of Delphi is that it is expensive and takes a very long time to complete. Even if it is paid, experts are always unwilling to meet in one place and at the same time. This situation makes the process even more difficult. Another disadvantage is that it determines the weight and priority of each parameter in a qualitative parameter. They recommend that the Delphi method should be developed due to such drawbacks (Ristono, Santoso, and Tama, 2018).

DEMATEL, one of the statistical approaches, is another method used to find the link between criteria and sub-criteria in supplier selection. With the DEMATEL, data are obtained through a questionnaire. The questionnaire is filled in by an expert. This method determines the importance of the criteria on each other. The results obtained from DEMATEL reveal the effect and relationship between the criteria (Orji, and Wei, 2014). Therefore, these two methods are combined as the DEMATEL results were found suitable for ISM entry. ISM and DEMATEL are good criteria selection methods, but they aren't good at listing the criteria that have been chosen. There is another disadvantage of using ISM and DEMATEL together. This combination does not take into account the weight of the criteria and takes longer to measure. In addition, it is not efficient to combine these two methods as they serve the same purpose (Ristono, Santoso, and Tama, 2018).

Structural equation modeling (SEM) is a more reliable method than ISM and DEMATEL. SEM is good at predicting the relationship between criteria. A structural model is used to establish this relationship. Three tasks can be performed by SEM simultaneously. These are the validity and reliability of the method, checking the latent criteria relationship model, and obtaining a useful prediction model (Sukwadi, and Yang, 2014). The confirmatory aspects of factor analysis, analysis of the road, and regression are all included in SEM. In this method, confirmative analysis is used rather than exploratory analysis. Since SEM focuses too much on affirming connections between criteria, it falls short in explaining relationships. Another drawback of SEM is that it is dependent on the theoretical rationale of structural models and route diagrams for calculation. However, sometimes a research area may not have been studied in the literature before. Given these drawbacks, ISM or DEMATEL is suitable for developing theory rationale in a specific field of study. The DEMATEL-SEM and ISM-SEM combined model is useful for evaluating supplier selection criteria (Ristono, Santoso, and Tama, 2018).

Ristono, Santoso, and Tama (2018) propose a new method for selecting criteria based on their studied literature. They suggest developing the Delphi model in the first step. This suggestion aims to save money. So, the change is that Delphi has been relocated to become a single round. ANOVA tests this solution in one round, and the questionnaire is given to each expert only once. Instead of gathering the surveyed experts in one place, they are visited by a responsible person. The second step is the development of a model according to the relevant criteria using DEMATEL or ISM. These models are used to show how the criterion relates to each other. It is then used with SEM to evaluate the linear relationships between observed and unobservable criteria to test the validity of the relevant ones. The PCA method is used in the third stage to evaluate all of the criteria in supplier selection. Finally, the weighting of criteria is calculated with MCDM methods and applied in the solution of the supplier selection problem.

Choosing the right criteria is another significant challenge in the supplier selection process. Selected criteria play an important role in evaluating suppliers. In the traditional supplier selection process, the price has always been the most important criterion in supplier evaluation (Degraeve, and Roodhooft, 1999). DMs are more likely to work with suppliers that made the lowest offer. However, it has been understood that evaluating suppliers only based on price criteria is not a strategic decision. Companies prefer to evaluate suppliers based on multiple criteria instead of evaluating them based on a single criterion (Mafakheri, Breton, and Ghoniem, 2011). Criteria in the selection of suppliers are examined under 3 aspects: economic, environmental, and social. These aspects, which are taken into consideration in supplier selection, contain hundreds of criteria in itself (Fallahpour et al., 2017). Determining and choosing the most suitable criteria for your company among these criteria significantly affects the success of the supplier selection process.

Dickson is one of our first researchers to deal with the economic aspect of supplier selection criteria. Dickson's studies are valuable to other researchers who address supplier selection criteria. While most of the researchers are conducting their work in this field, they draw attention to Dickson's work in their articles. Dickson (1966) conducts a case study on four different companies' supplier selection criteria. They prepared a list of 23 criteria for this case study that they can use when evaluating and choosing suppliers. They sent this list to experts in their field and asked them to make a choice ranking for these four companies. As a result of the feedback they received from experts, they identified the two most important criteria in the supplier selection process as quality standards and delivery schedules. Following these two criteria, the most important other criteria are listed as follows; performance history,

warranties and demand policies, production facilities and capacity, price, technical competence, and finally financial situation. In Dickson's (1966) case study, the criteria preferred for each company were different. For example, the importance of the price criterion for one company ranks in the top three, while it turned out to be much less important for another company. In this study, the criteria varied according to the purchasing decision status for each company (Dickson, 1966). The purchasing decisions and priorities of companies may differ from each other. For this reason, it is useful to consider the purchasing status of the company when determining and choosing the supplier selection criteria.

To provide a detailed overview of supplier selection criteria, Weber, Current, and Benton (1991) review the purchasing literature from 1966 to 1991. They limit their literature study on industrial buyers' supplier selection. They examined 74 articles from the retail and manufacturing industries that dealt with supplier selection criteria. They find that in most of the articles they review, more than one criteria was discussed. In other words, a single price criterion is not emphasized in these articles as in the traditional supplier selection process. As a result of their literature review, Weber, Current, and Benton (1991) find that quality, cost, and on-time delivery criteria are the three major supplier selection criteria. They also find that the supplier selection process has undergone major improvements, including improved quality guidelines, computer communication, and technological capabilities. People became interested in just-in-time (JIT) manufacturing methods as a result of these improvements. In response to this increasing interest, Weber et al. (1991) discuss the impact of JIT on supplier selection criteria in their articles. They conduct a study of the effect of JIT on supplier selection since the implementation of JIT may require a reordering of criteria from which suppliers are selected. As a result, they find that their production facilities and capabilities are an important JIT criterion. They also list the important criteria for JIT respectively as follows; production facilities and capabilities, net price, geographical location, technical capability, attitude, management, and organization, operational controls, service, and finally packaging (Weber, Current, and Benton, 1991).

Choi, and Hartley (1996) conduct a survey of companies at different levels to evaluate supplier selection methods in the automotive industry. First, they sent this survey to people from the academy to verify the content, and they asked for feedback on the survey. Second, they review the survey with expert purchasing managers in their field to make sure the survey questions are interpreted as intended and in the same way. Purchasing managers surveyed are asked to focus on the situation as if they are purchasing a new major component part. Thus, they believe that the survey's results would be more valuable because they would test the survey in a real-life environment. Respondents are asked to choose from the lowest to the highest priority over 26 supplier selection criteria. The 8 most important criteria among the 26 are identified as follows: finances, consistency, relationship, flexibility, technological capability, customer service, reliability, and price as a result of this survey. As a result of this research, Choi, and Hartley (1996) came to some conclusions. They conclude that the automotive industry needs to choose suppliers based on the likelihood of a long-term partnership. They also conclude that one of the least important criteria is price. Furthermore, they conclude quality and delivery as one criterion in their report, contrary to popular belief that they are two separate criteria (Choi, and Hartley, 1996).

Ho, Xu, and Dey (2010) conduct a literature review to identify the most commonly used criteria by DMs when evaluating and choosing the supplier. As a result of this literature review, they realize that hundreds of criteria are used in supplier selection. Among these criteria, they list the most commonly used criteria as follows; quality, delivery, price/cost, manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety, and environment. They realize that each of these listed criteria contains subcriteria among themselves. While determining the supplier selection criteria, it is important to determine the content of these sub-criteria in the supplier selection problem. For this reason, the sub-criteria of the three most important criteria is shown as follows. Quality, the most widely used criterion, refers to the following subcriterion; compliance with quality, low defect rate, number of qualified staff, process control capability, quality assurance production, quality award, quality certification, reliability of quality, rejection in incoming quality, rejection in the production line, rejection from customers, shipment quality, and training, etc. Delivery, the second most widely used criterion, refers to the following sub-criteria; compliance with a due date, delivery and location, delivery conditions, delivery

delays, delivery lead time, delivery mistakes, delivery reliability, distance, geographical location, number of shipments to arrive on time, order-to-delivery lead time, on-time delivery, etc. Price, the third most popular criterion, is listed as follows; appropriateness of the materials price to the market price, competitiveness of cost, direct cost, logistics cost, manufacturing cost, unit cost, ordering cost, parts price, product price, and total cost of shipments, etc. While determining supplier selection criteria, it is equally important to select and define these sub-criteria. The literature review by Ho, Xu, and Dey (2010) reveals that price is not the most important criterion. In contemporary purchasing management, it has become clear that the traditional single criteria method that focuses on the lowest cost bidding is no longer sufficient (Ho, Xu, and Dey, 2010).

There is a wide literature on supplier evaluation and selection. So many studies have been done in this area. However, there is limited research available on environmental issues in green supplier evaluation. Govindan et. al. (2015) conduct a study based on this gap, addressing only the environmental aspects of supplier selection criteria. For this reason, they do not consider traditional supplier selection criteria in this study. They find that environmental management systems are the most commonly used criterion for selecting green suppliers as a result of their study. Subsequently, they list the most popular environmental criteria as follows; green image, environmental performance, environmental competencies, design for environment, green competencies, corporate and social responsibilities, environmental efficiency, environmental authentication, environmental improvement cost, green logistic dimension, green organization activities, environmental certification, suppliers' green image, use of environmentally friendly material, use of environmentally friendly technology, waste management, re-use, re-cycle, green process innovation, green product, green purchasing, green project partnership, and green design. With this study, they present a list of criteria for selecting environmentally friendly suppliers. It is of utmost importance to make an assessment that addresses the social criteria when evaluating green suppliers. Govindan et. al. (2013), in their previous study, listed the popular supplier selection criteria by considering the social aspects. These are discrimination, long working hours, human rights, health and safety, disclosure of information, rights of stakeholders, employment practices. Govindan et. al.

contribute to the evaluation of green suppliers with these articles. These articles are valuable studies in evaluating green suppliers.

Fallahpour et. al. (2017) conduct a study to develop the most important and applicable criteria for supplier selection and corresponding sub-criteria. They carry out this study through a survey. They handle this survey study in four parts in total. In the first part, they ask questions to gather information about the survey participants. In the second, third, and fourth sections, they ask questions that, respectively, included economic, environmental, and social aspects criteria and their sub-criteria. They sent the questionnaire to seven experts in research and business to make sure the content is correct. The survey has been revised many times as a result of experts' comments and feedback. As a result of these revisions, the survey is completed and approved by the same experts. As a result of the survey, Fallahpour et. al. (2017) find that among the 46 sub-criteria, the most common criteria are material cost, the rejection rate of the product, freight cost, the capability of handling abnormal quality, and the process for internal audit quality material. They list the most important criteria in real life as follows; quality, cost, delivery, and service. In addition to these, they stated that environmental management systems and workers' rights are among the important criteria. To prove the accuracy of the data obtained from the questionnaire, Fallahpour et. al. (2017) apply Cronbach's alpha and the Mann-Whitney U-Test. They prove that the survey data obtained as a result of these tests created reliable results. As a result of their study, they find that the economic aspect is still the most popular supplier selection criteria. After the economic aspect, they determine that the environmental and social aspects included the most important criteria (Fallahpour et al., 2017).

The most significant step in building a decision-making model, according to Song et. al. (2017), is criteria selection. They suggest that suppliers be selected based on criteria based on the company's activity and match the factors in their environment. They further recommend that when making a decision, producers' psychological behavior be considered and the use of low-risk, flexible working concepts. In other words, they point to the importance of suppliers who have the ability to cope with risk and adapt to flexible production conditions. In addition to these, they list the criteria commonly used in the literature as follows; quality, delivery, price, manufacturing capability, service, management, technology, research, flexibility, finance, reputation, relationship, risk and safety, and the environment (Song et al., 2017).

Khemiri et. al. (2017) propose a set of sub-criteria for evaluating the success and risk of a procurement development plan. First, they select a set of criteria aimed at evaluating the performance of a plan. These are cost, number of actors, quality, and reliability. These criteria measure the performance of suppliers who can react to changes. It allows differentiating other suppliers who may have difficulty coping with unexpected events. Khemiri et al. (2017) define these criteria as follows. Cost: It refers to costs of production, outsourcing, and buying costs. It may not be possible to extract these costs in the short term. A number of actors: refers to suppliers, production facilities, and subcontractors involved in a plan. Some companies assume that lowering the number of suppliers would help them improve quality while lowering costs. Quality: It refers to the partners' ability to deliver parts that meet the criteria in the packaging conditions. Reliability: expressed as a supplier's ability to deliver orders on time. These mentioned criteria are decision criteria based on performance. They list the risk-based decision criteria as follows: flexibility, responsiveness, robustness, resilience, and stability. Flexibility: A supplier's flexibility is described as its ability to handle changes in product requirements enforced by the consumer while the demand is being processed. Responsiveness: Refers to the supplier's potential to reply to a shift in order due dates. Robustness: The insensitivity of a supplier to disruptions can be described as its robustness. Resilience: Khemiri et. al. (2017) define resilience as an individual's ability to return to a satisfactory state following a crisis. This definition is taken from Cyrulnik, and Macey (2009). Stability: A supplier's stability is defined by planning rather than the supplier. Measures the consistency of a supplier's performance over two periods of time. Among all these criteria, quality, reliability, flexibility, responsiveness, robustness, and resilience are utility criteria and these criteria should be maximized. Cost, number of actors, and instability are cost criteria that should be minimized (Khemiri et. al., 2017).

Nong, and Ho (2019) conduct a study aimed at investigating criteria for supplier selection in the textile and apparel industry in Vietnam. Supplier selection criteria in

the textile and apparel industry have been mostly examined through literature reviews. Nong, and Ho (2019) describe these criteria using a methodology that combines a qualitative and a quantitative approach. Nong, and Ho (2019) cite the importance of a flexible supply chain that responds quickly to customer needs due to the short life cycle of the textile and apparel industry with this article. Based on the data they obtained as a result of their literature review, they prepare a list consisting of 27 criteria and 178 sub-criteria. Then, they sent this list to practitioners. According to the data they obtained from the practitioners, they see that organizational factors consisted of the supplier's capabilities, relations with buyers, and corporate social responsibilities. They determine the most important criteria in the textile and apparel industry as quality, cost, delivery, service, capability, company's image, relationship, and sourcing country. Choosing the right supplier or suppliers is a difficult process for DMs. The criteria chosen when evaluating the suppliers are often in conflict with each other. MCDM approach is applied to handle and solve these criteria easily. The MCDM approach is handled in four stages in total, by determining alternative suppliers, determining criteria, calculating the weight of each criterion, and calculating the performance of each alternative supplier in terms of criteria. Defining and selecting supplier selection criteria is an essential step in problem-solving. In this area, each criterion has sub-criteria that enables it to be determined in more detail. Nong, and Ho (2019) cannot determine the weights and sub-criteria of the criteria as a result of a literature review. They realize that there is a lack of literature on this subject. Therefore, they suggest more MCDM-based studies on these weights (Nong, and Ho, 2019).

Choosing the right supplier selection criteria is an indispensable part of the supplier selection process. The importance of selection criteria may differ for each company. Among these numerous criteria, which are divided into 3 groups in terms of economic, social, and environmental aspects, the area that still has the highest importance today is the economic aspect.

# **CHAPTER 3: METHODOLOGY**

In the literature review section, we discuss the methods and criteria used in supplier selection. We also analyze the methods in terms of compensation among criteria.

Decision-making methods can be divided into two categories; compensatory methods and non-compensatory methods. A compensatory method appreciates the supplier's high success in a criterion and allows this success to compensate for its moderate or low value in another criterion. On the other hand, a non-compensatory method also appreciates the supplier's high success in a criterion, but does not allow this success to compensate for another criterion (Rothrock, and Yin, 2008). To the best of our knowledge, there is no study that uses a non-compensatory method for the supplier selection problem. The articles we have reviewed propose compensatory methods for the problem. However, we believe that using a compensatory method may not be enough to represent the preferences of DMs.

In the methodology section, we cover three topics; first, we handle the multiobjective sorting problem. In the corresponding subsection, we discuss (i) how to sort with the linear value function, which is a compensatory method and (ii) how sorting is done with MR-Sort, which is a non-compensatory method. We explain with examples to clarify the difference between this compensatory linear value function and non-compensatory MR-Sort methods. Second, we discuss the weight space of a multiobjective problem. When studying a 3-criteria supplier selection problem with a linear value function, we have a 2-dimensional weight space. We discuss our two-dimensional weight space with various triangles. Finally, we consider the consistency check of the DM preferences gathered via the web survey. In the last subsection, we discuss the mathematical models of the linear value function and the mathematical models of the MR-Sort methods used for the consistency check.

### 3.1 Multiobjective Sorting

Multiobjective sorting aims to assign a group of alternatives evaluated with multiple objectives to ordered classes. In this section, we assign our suppliers to classes using the multiobjective sorting method. We define three classes, rejected suppliers (worst), shortlisted suppliers (middle), and accepted suppliers (best). The worst class is the group with the worst suppliers and, we do not recommend working with these suppliers. For suppliers assigned to the middle class, we recommend that it may be possible to work as a result of certain improvements. Finally, we recommend that it should definitely work with the suppliers in the best group. Our aim here is to assign each supplier to one of these classes based on the preferences of the DM.

We assign suppliers to one of these classes using the sort method;  $C = \{C_1, C_2, \dots, C_t\}$  where  $C_h >> C_{h-1}$ , for h = 2, ..., *t*. The function  $C_1$  represents the worst class, while the function  $C_t$  represents the best class.  $O = \{o_1, o_2, \dots, o_q\}$  refers to a set of suppliers. Each suppliers  $o_i$  is evaluated with a certain set of criteria  $N = \{q_1, \dots, q_n\}$  with the scores  $o_i = \{o_{i1}, o_{i2}, \dots, o_{in}\}$ . Without loss of generality, we assume a higher score is better in each criteria. Using this formulation, in a system where three criteria are used in supplier selection, we ask the DMs to preference by making pairwise comparisons by providing the scores of the suppliers on these three criteria.

#### 3.1.1 Sorting with The Linear Value Function

In this section, we discuss how we sort suppliers with the linear value function. The value of an alternative is computed using the linear method, which is a compensatory method, as the weighted sum of each criteria score (Mousseau, Özpeynirci, and Özpeynirci, 2018). We describe the total value of a supplier with the following function;

$$U(o_i) = \sum_{j=1}^n w o_j i_j$$

The function  $U(o_i)$  represents the value of supplier *i* and the parameter *w* represents the weight of the criterion *j*. The value  $o_{ij}$  represents score of supplier *i* on criterion *j*. Using this formula, we find the utility of each supplier. After finding the total utility provided by each supplier, these suppliers are assigned to various classes. The utility values are compared to the class thresholds to assign the suppliers to one of the classes (Mousseau, Özpeynirci, and Özpeynirci, 2018). With a linear value function, we assign our alternatives to various classes with the following rules;

$$U(o_{i}) \geq b^{t-1} \rightarrow o_{i} \in C_{t}$$

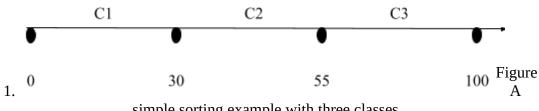
$$b^{h-1} \leq U(o_{i}) < b^{h} \rightarrow o_{i} \in C, \quad h = 2, 3, \dots, t-1$$

$$i_{t} \quad U(o_{i}) < i_{t}^{i} \quad h \in C,$$

$$i_{t} \quad b \rightarrow o_{i} \quad t$$

We define  $b^h$  as the upper bound value for class  $C_h$ . We calculate which class the suppliers belong to with this mathematical model. If the utility of a supplier is higher than the upper bound of second best class  $\binom{t-1}{b}$  we assign the supplier to the best class. If the utility of a supplier falls within the upper and lower bounds of a class, we assign that supplier to that class. If the utility of a supplier is lower than the upper bound of the worst class, we assign that supplier to the supplier to the utility of a supplier to the utility of a supplier to the utility of a supplier to the utility of a supplier to the utility of a supplier to the upper bound of the worst class, we assign that supplier to the worst class.

Let's consider a group of suppliers assigned to classes with a linear value function. Figure 1 shows us that if the total utility of a supplier is less than 30, we assign that supplier to the worst class. If the total utility is greater than or equal to 30 and less than 55, we assign that supplier to the middle class. If the total utility is greater than or equal to 55, we assign that supplier to the best class. Hence for this illustrative example,  $b^1 = 30$  and  $b^2 = 55$ . With the linear value function, we assign suppliers to one of these ranges where their total utility corresponds.



simple sorting example with three classes.

Figure 1. shows how we sort a set of suppliers with a linear value function with an example of a three-class sorting. For example, suppose a supplier has a total score of 25 calculated by the linear value function. In such a case, we assign this supplier to the worst class. We do not recommend working with suppliers in this class. If another alternative supplier has a total score of 60, we assign it to the best class and recommend working with those suppliers. Suppose the total value of one supplier from our supplier group is 50. In such a case, we assign this supplier to the middle class, as it cannot exceed the upper limit, and recommend that it may be possible to work with this supplier as a result of some improvements.

### 3.1.2 Sorting with The MR-Sort

In this section, we discuss how to sort a group of suppliers using the Majority Rule Sorting (MR-Sort) method. MR-Sort is a simplified version of ELECTRE-TRI and it assigns alternatives to various classes. MR-Sort uses the majority rule to calculate the class to which an object is assigned (Bouyssou, and Marchant, 2007; Leroy, Mousseau, and Pirlot, 2011; Özpeynirci, Özpeynirci, and Mousseau, 2020). There are several classes in this method, and each class has a profile defined for each criterion.

We calculate how sorting is done with MR-Sort, which is a non-compensatory method, using these formulas. In the formula, the parameter  $\lambda$  shows the cut level and,  $b^{h}$  represents the criterion *q* upper bound value for each class *C*. This formula indicates that the supplier is in the best class if the sum of the weights of the criteria better than the lower limit of the best class is greater than w;

$$\sum_{\substack{o_{ij} \geq b_j^{i-1}}} w_j \geq \lambda \to o \underset{i}{\in} C .$$

If the sum of the criterion weights for which the supplier score is better than lower

limit of class  $C_h$  is greater than the threshold value, but less than the upper limit of class  $C_h$ , this supplier is assigned to class  $C_h$ ;

$$\sum_{\substack{j \in N: o \geq b \\ ij \neq j}} w_j \geq \lambda \text{ and } \sum_{\substack{j \in N: o \geq b \\ ij \neq j}} w_j \prec \lambda \to o \underset{i}{\in} C_h.$$

If the sum of the weights of the criteria better than the lower limit of the worst class is less than the threshold value, this supplier is in the worst class;

$$\sum_{\substack{o \geq b^1 \\ ij \quad j}} w \prec \lambda \to o \atop ij \quad ij \quad 1$$

We sort our suppliers with the MR-Sort method, which is a non-compensatory method with these formulas.

#### **3.1.3** Simple Examples

In this section, to better explain the difference between compensatory and noncompensatory methods, we give two simple examples that include linear value function and MR-Sort methods.

Let's consider an example consisting of a group of students to be evaluated on a course using the weighted sum method. Each student is evaluated using three criteria: in-class performance (20%), midterm exam (30%), and final exam (50%). Each student is evaluated between 0 (worst) and 100 (best) for all three criteria. For a student to be considered successful, the sum of the weights of these 3 criteria must be higher than 60. Let's assume that a student we evaluate with a weighted total gets 30 points in-class performance, 50 points in the midterm exam, and 80 points in the final exam. If this student is evaluated with a compensatory method, the high score she gets from the final exam compensates for her low grade for in-class performance. This student, whose weighted average is calculated, gets a total of 61 points and enters the category of a successful student. On the other hand, if we evaluate this

student in a non-compensatory method, we do not allow her success in the final exam to compensate for her failure in class performance. A lower bound comes into play when evaluating with a non-compensatory method. In this method, we do not consider the weights of scores that fall below a predetermined bound. Suppose this lower bound is 45 points. In other words, if a student's score is 45 or less in some criterion, we will not add the weight of the corresponding criterion to the total score. For this reason, we will not consider the weight of in-class performance for this student, who scored 30, on this criterion. We will calculate the weights of this student's scores only in the midterm and final exams. When we calculate the weights of the points this student got on these two criteria, this student reaches 55 points in total. The 55 points collected by this student are below the total of 60 required for a student to be considered successful. As a result, this student is not considered successful because she could not collect a total of 60 points when evaluated with the non-compensatory method. In other words, this student who was successful with the compensatory method was deemed unsuccessful when evaluated with a noncompensatory method. This short example shows us the possibility that the supplier we consider successful when evaluating suppliers may fail when we evaluate them with a non-compensatory method.

In the literature, compensatory methods are generally used in supplier selection. We claim that in real life, we may encounter situations where we cannot explain the preferences of the DM using the linear value function method. We aim to prove that there are situations that cannot be explained with a linear value function but can be explained with MR-Sort.

In addition to the example of a group of students we covered with the linear value function, we give you an example of a hotel. With this example, we try to explain the classification with the MR-Sort method more clearly. Let's assume that we evaluate 5-star hotels on 3 criteria. Let these criteria be the number of restaurants, room size, and service quality. In the restaurant number criteria, there should be at least 8 different restaurants. For the room size criterion, there should be an area of at least 150 square meters. Service quality must be at least 4 points out of 5. In the MR-Sort method, if a hotel meets these conditions, it receives 5 stars. If this hotel meets some of the criteria but cannot meet others, an evaluation is made for a subclass. If the

alternative evaluated is better than the profile value in most of these criteria, for example, if it is better than the minimum required to become a 5-star hotel, it is assigned to the best class. In other words, if the sum of the weights of the criteria for which the profile has a better value than the lower limit is greater than the lambda value, we say to which class this alternative belongs. If this criterion does not meet the best class, we evaluate for a subclass. If the sum of the weights exceeds lambda for a subclass, we say it is in that class. We can make these assessments down to the worst grade because we can assign each alternative to the worst class. However, we are always trying to find the best class that an alternative can be assigned (Özpeynirci, Özpeynirci, and Mousseau, 2020).

In real life, we may encounter situations where we cannot explain the preferences of DMs with compensatory methods, for example, with a linear value function. In such a case, we can overcome this problem by using non-compensatory methods such as MR-Sort.

## 3.2 Weight Space Decomposition

In multiple criteria decision making, we can discuss different spaces, one of these spaces is the weight space. For a problem with three criteria, the weight space is 2 dimensional. We can graphically represent preferences of the decision maker in the weight space assuming the linear value function.

This weight space of ours is 2-dimensional. We calculate the size of this weight space by subtracting 1 from our number of criteria. The sum of the weights of these 3 criteria is equal to 1 ( $w_1 + w_2 + w_3 = 1$ ). We represent our weight space with the triangle in Figure 2.

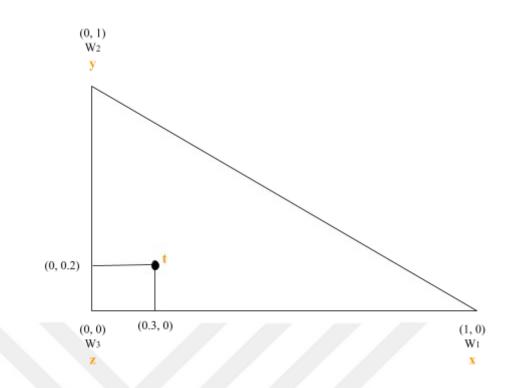


Figure 2. Weight Space.

The weights in Figure 2. are as follows; at point z,  $w_3 = 1$ , and  $w_1 = w_2 = 0$ , at point x,  $w_1 = 1$ , and  $w_2 = w_3 = 0$ , at point y,  $w_2 = 1$ , and  $w_1 = w_3 = 0$ . For example, at point t,  $w_2 = 0.2$  and  $w_1 = 0.3$ ,  $w_3 = 0.5$ , because the sum of the weights of these 3 criteria is equal to 1.

In a system where three criteria are used for supplier selection, we ask the DMs questions with the pairwise comparison method. We expect DMs to choose one of these two options each time. The performance scores of all suppliers are evaluated between 0 (worst) and 100 (best) for all three criteria. In each criterion, a higher value is preferable. For example; Let's call the first supplier A and the second supplier B. The scores of suppliers A and B on 3 criteria are A= (21, 47, 82) and B= (24, 47, 79). We ask the DM to consider the first criterion as the most important criterion for herself, the second criterion as the moderately important, and the third criterion as the least important criterion. Based on this mapping, we ask the DM to select one of these suppliers.

Alternatives	Most important	Moderately important	Least important
А	21	47	82
В	24	47	79

Table 1. Pairwise Comparison.

We find utility created by a supplier by the score times the weight (utility = score x weight). When we equalize the benefits of each of the 2 suppliers we find, we find the line formed in the triangle (U(A) = U(B)). This is how we calculate;

 $U(A) = 21w_{1} + 47w_{2} + 82w_{3}$   $U(B) = 24w_{1} + 47w_{2} + 79w_{3}$ Then setting U(A) = U(B),  $21w_{1} + 47w_{2} + 82w_{3} = 24w_{1} + 47w_{2} + 79w_{3}$   $3w_{3} = 3w_{1}$   $w_{3} = w_{1}, \text{ by setting } w_{3} = 1 - w_{1} - w_{2}$   $1 - w_{1} - w_{2} = w_{1}$   $2w_{1} + w_{2} = 1.$ 

In Figure 3., equating the benefits of suppliers A and B, we found the line dividing the triangle from the middle at 0.5 points.

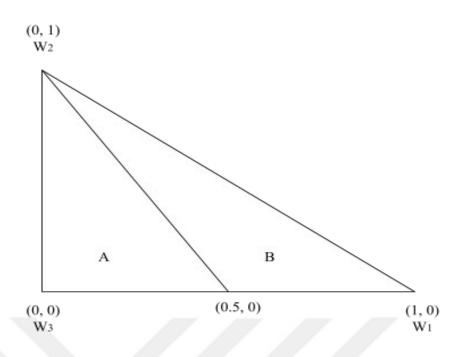


Figure 3. Pairwise Comparison Example 1.

Figure 3. shows us which supplier is better within the triangle. After the DM has made her or his preference, we continue with another question in that triangle. Suppose the DM prefers supplier A (21, 47, 82) to B (24, 47, 79). As a second question, we ask the following pairwise comparison question. Which supplier would you prefer; C (12, 46, 90) or D (20, 46 87)?

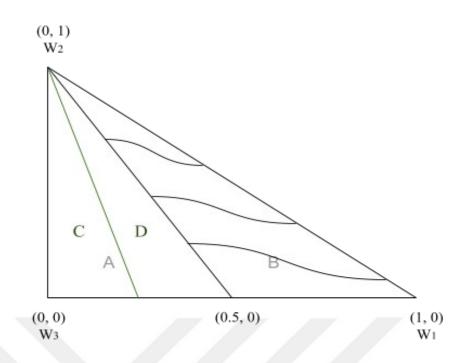


Figure 4. Pairwise Comparison Example 2.

When the DM prefers supplier A, we have excluded the other half of the triangle from our solution space. We show the area we are not working on with the curved connector. Figure 4. shows the new areas formed in triangle A when we ask the second question to the DM. The DM must prefer between these two fields to be consistent with any value function. With the DM choosing supplier C or D, the field we are working on is getting narrower. In this way, we ask a total of 12 pairwise comparison questions to the DM. After each question we ask, the area we work in the triangle narrows.

As long as the DM provides new preferences within the appropriate areas in the triangle, we can explain the DM preferences with a linear value function. However, if the DM makes a new decision outside the appropriate area in the triangle, we cannot explain the preference of the DM with a linear value function. For example, in the comparison of suppliers C and D, the DM preferred supplier D. As the next 3rd question, we compare suppliers E and F. With the 3rd question, our new area inside the triangle is as in Figure 5.

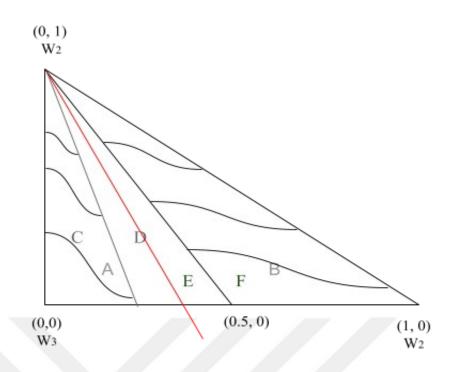


Figure 5. Pairwise Comparison Example 3.

Under normal circumstances, the DM, whose preferences can be explained by a linear decision function, is expected to choose supplier E within the triangle in such a question. However, if the DM chooses supplier F in such a question, then we conclude there is an inconsistency. In such a case, we say that a linear value function is insufficient to explain the preferences of the DM.

After each of the four questions, we designed the next 2 questions in a way that could mislead the DMs. DMs who make preferences with a linear value function will make consistent preferences by not being deceived by these misleading questions. DMs who cannot make preferences with any linear value function are likely to reach inconsistent results. We tried to understand the evaluation methods in the minds of the decision makers with these questions.

#### 3.3 Consistency Check

In this section, we construct models that examine whether DMs' preferences can be explained with a linear value function and the MR-Sort method. We examine whether we can explain the preferences of DMs that cannot be explained by a linear value function, which is a compensatory method, using the non-compensatory MR-Sort method. We present the mathematical model we use for the linear value function and the mathematical model we use for MR-Sort under two headings.

#### 3.3.1 The Mathematical Model We Use for The Linear Value Function

A model to check if there is a weight set that explains the preferences of the DM. We constructed this mathematical model to check whether we can explain DM preferences with a linear value function.

Index *i* represents the pairwise comparison questions and index *q* represents the criteria. Binary variable *y* gets the value of 1 if  $i^{th}$  pairwise comparison is removed and 0 otherwise. Continuous variable *w* represents the weight of criterion *q*.

$$minimize \sum_{i=1}^{12} y_{i=1}$$
(1)

subject to

$$\sum_{q=1}^{3} x w^{2} \sum_{q=1}^{3} x w^{2} - My$$

$$i = 1, \dots, 12$$

$$i = 1, \dots, 12$$

$$(2)$$

$$\sum_{q=1}^{3} w_{q} = 1$$
(3)

$$?_q \ge 0 \tag{4}$$

 Objective function (1) aims to minimize the number of removed responses.

Constraint set (2) assumes the DM's prefers supplier  $x^{1} = (x_{i1}^{1}, x_{i2}^{1}, x_{i3}^{1})$  to supplier  $?_{i}^{2} = (x_{i1}^{2}, x_{i2}^{2}, x_{i3}^{2})$  as the response of ith comparison and forces the utility of supplier  $x^{1}$  to be at least as good as supplier  $x_{2}^{2}$  if the response is not removed. If the corresponding response is removed, the constraint becomes redundant. Constraint (3) ensures the sum of the weights add up to one. Constraint sets (4) and (5) define nonnegative weights and binary decision variables for response removal. Figure 6. represents the GAMS implementation of the model for an instance.

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<pre>z objective function value Positive Variables w(j) weight of criterion j binary variable y(i) 1 ff DM response is deleted ; Equations obj objective function c0 c1 c2 c3 c4 c5 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c6 c7 c7 c7 c7 c7 c7 c7 c7 c7 c7 c7 c7 c7</pre>		
<pre>Positive Variables w(j) weight of criterion j binary variable y(i) 1 ff DM response is deleted ; Pquations obj objective function c1 c2 c3 c4 c5 c6 c7 c8 c9 c10 c11 c12; c2 c3 c4 c5 c6 c7 c3 c4 c5 c6 c7 c3 c4 c5 c6 c7 c3 c9 c10 c11 c12; c1. stw(11)/j=s=1; c1. stw(12)/j=s=1; c1. stw(12)/j=s=1; c1. stw(12)/j=s=1; c1. stw(12)/j=s=0; c2 8*w(12)/j=s=0; c3. + c1*w(12)/j=s=0; c3. + c1*w(12)/j=s=0; c3. + c1*w(12)/j=s=0; c3. + c1*w(12)/j=s=0; c4 26*w(11)/j=sw(12)/j=s=0; c5 23*w(12)/j=sw(12)/j=sw(13)/j=s=0; c5 c1*w(12)/j=sw(12)/j=sw(13)/j=s=0; c5 c1*w(12)/j=sw(12)/j=sw(13)/j=s=0; c5 c1*w(12)/j=sw(13)/j=s=0; c5 c1*w(12)/j=sw(13)/j=s=0; c1 s*w(12)/j=sw(12)/j=s=0; c1 s*w(12)/j=sw(12)/j=s=0; c1 s*w(12)/j=sw(12)/j=s=0; c1 s*w(12)/j=sw(12)/j=s=0; c1 s*w(12)/j=sw(12)/j=s=0; c1 s*w(12)/j=sw(12)/j=sw(13)/j=s=0; c1 s*w(12)/j=sw(12)/j=sw(13)/j=sw(13)/j=s=0; c1 s*w(12)/j=sw(12)/j=sw(13)/j=s=0; c1 s*w(12)/j=sw(12)/j=sw(13)/j=sw(12)/j=s=0; c1 s*w(12)/j=sw(12)/j=sw(13)/j=sw(12)/j=s=0; c1 s*w(12)/j=sw(12)/j=sw(12)/j=sw(12)/j=s=0; c1 s*w(12)/j=sw(12)</pre>		
<pre>w(j) weight of criterion j binary variable y(i) 1 if DW response is deleted; Equations obj objective function c0 c1 c2 c3 c3 c4 c5 c6 c6 c7 c8 c9 c10 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1. 3*w(r1")-3*w(r3")+1000*y(r1")=E=0; c2 sum(j,w(j))=E=1; c1. 3*w(r1")-3*w(r3")+1000*y(r2")=G=0; c3. +21*w(r2")-20*w(r3")+1000*y(r3")=G=0; c3. +21*w(r2")-20*w(r3")+1000*y(r4")=E=0; c3 25*w(r1")+5*w(r3")+1000*y(r6")=E=0; c3 25*w(r1")+25*w(r3")+1000*y(r6")=G=0; c3 21*w(r2")-84*w(r3")+1000*y(r6")=G=0; c3 21*w(r2")-84*w(r3")+1000*y(r6")=G=0; c3 21*w(r1")+25*w(r3")+1000*y(r10")=E=0; c3 21*w(r1")+25*w(r3")+1000*y(r10")=E=0; c3 21*w(r1")+25*w(r3")+1000*y(r10")=E=0; c3 21*w(r1")+25*w(r3")+1000*y(r10")=E=0; c1 1*w(r1")+23*w(r2")+25*w(r3")+1000*y(r10")=E=0; c1 1*w(r1")+23*w(r2")+25*w(r3")+1000*y(r10")=E=0; c1 28*w(r1")+25*w(r3")+1000*y(r11")=G=0; c128*w(r1")+25*w(r3")+1000*y(r11")=G=0;		
<pre>binary variable y(i) 1 if DW response is deleted ; Equations obj objective function cl cl cl cl cl cl cl cl cl cl cl cl cl</pre>		
<pre>y(i) 1 if DM response is deleted ; Fquations Obj objective function C1 C2 C3 C4 C5 C6 C7 C8 C9 C10 C11 C11 C11 C1 C1 C1 C1 C1 C1 C1 C1 C1</pre>		
<pre>Equations Obj objective function C0 C1 C2 C3 C4 C5 C6 C7 C8 C9 C1 C1 C2 C3 C4 C5 C6 C7 C8 C9 C1 C1 C1 C1 C1 C2 C2 C3 C4 C4 C4 C5 C6 C7 C7 C8 C9 C1 C1 C1 C1 C1 C2 C2 C3 C4 C4 C4 C4 C4 C4 C4 C4 C4 C4 C4 C4 C4</pre>		
<pre>Obj objective function Cl Cl Cl Cl Cl Cl Cl Cl Cl Cl</pre>		
<pre>c0 c1 c2 c3 c4 c5 c6 c6 c7 c6 c9 c10 c11 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1*)-3*w("3*)-1000*y("1*)=L=0; c1 3*w("1*)-3*w("3*)+1000*y("2*)=G=0; c3 +21*w("2*)-20*w("3*)+1000*y("3*)=G=0; c3 +21*w("2*)-20*w("3*)+1000*y("4*)=G=0; c3 +21*w("2*)-20*w("3*)+1000*y("3*)=G=0; c426*w("1*)+9*w("2*)-34*w("3*)+1000*y("4*)=G=0; c5 23*w("1*)+9*w("2*)-34*w("3*)+1000*y("5*)=G=0; c6 +0*w("1*)-2*w("2*)+100*y("3*)+1000*y("1*)=G=0; c6 +3*w("2*)-3*w("3*)+1000*y("1*)=G=0; c7 +3*w("2*)-3*w("3*)+1000*y("10*)=L=0; c10 11*w("1*)-30*w("2*)+26*w("3*)+1000*y("10*)=L=0; c11 9*w("1*)+25*w("2*)+26*w("3*)+1000*y("12*)=G=0; c1228*w("1*)+25*w("2*)+1000*y("12*)=G=0; model TezModeli /all/; solve TezModeli /all/;</pre>		
<pre>c1 c2 c3 c3 c4 c5 c6 c7 c7 c8 c9 c10 c11 c12; c0 sum(j,w(j))=E=1; c1 3*w("1")-3*w("3")-1000*y("1")=L=0; c28*w("1")+3*w("3")-1000*y("2")=G=0; c3 +21*w("2")-20*w("3")+1000*y("3")=G=0; c426*w("1")+1*w("2")+30*w("3")+1000*y("4")=G=0; c5 23*w("1")+9*w("2")-20*w("3")+1000*y("6")=G=0; c426*w("1")-11*w("2")+30*w("3")+1000*y("6")=G=0; c5 23*w("1")+28*w("2")+25*w("3")+1000*y("6")=G=0; c7 +3*w("2")-3*w("3")+1000*y("7")=G=0; c8 +3*w("2")-3*w("3")+1000*y("6")=L=0; c10 11*w("1")-30*w("2")+23*w("3")+1000*y("10")=L=0; c10 11*w("1")-30*w("2")+23*w("3")+1000*y("11")=G=0; c1128*w("1")+5*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli /all/;</pre>		
<pre>C2 G3 G4 G5 G6 G7 C7 C8 G9 C10 C11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3<sup>x</sup>w("1")=3<sup>x</sup>w("3")=1000<sup>x</sup>y("1")=L=0; c28<sup>x</sup>w("1")=3<sup>x</sup>w("3")=1000<sup>x</sup>y("2")=G=0; c3 +21<sup>x</sup>w("2")=20<sup>x</sup>w("3")+1000<sup>x</sup>y("3")=G=0; c3 +21<sup>x</sup>w("2")=20<sup>x</sup>w("3")+1000<sup>x</sup>y("3")=G=0; c3 +21<sup>x</sup>w("2")=20<sup>x</sup>w("3")+1000<sup>x</sup>y("5")=G=0; c3 +21<sup>x</sup>w("2")=20<sup>x</sup>w("2")+25<sup>x</sup>w("3")+1000<sup>x</sup>y("6")=G=0; c5 23<sup>x</sup>w("1")=1<sup>x</sup>w("2")=20<sup>x</sup>w("3")+1000<sup>x</sup>y("5")=G=0; c610<sup>x</sup>w("1")=28<sup>x</sup>w("2")+25<sup>x</sup>w("3")+1000<sup>x</sup>y("6")=G=0; c7 +3<sup>x</sup>w("2")=3<sup>x</sup>w("3")+1000<sup>x</sup>y("5")=G=0; c921<sup>x</sup>w("1")+20<sup>x</sup>w("2")+20<sup>x</sup>w("3")+1000<sup>x</sup>y("1")=L=0; c10 11<sup>x</sup>w("1")=30<sup>x</sup>w("2")+25<sup>x</sup>w("3")+1000<sup>x</sup>y("10")=L=0; c11 9<sup>x</sup>w("1")+25<sup>x</sup>w("2")=10<sup>x</sup>w("3")+1000<sup>x</sup>y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
<pre>c3 c4 c5 c6 c7 c8 c9 c10 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1")-3*w("3")-1000*y("1")=L=0; c203*w("1")+3*w("3")+1000*y("2")=G=0; c3 +21*w("2")-20*w("3")+1000*y("3")=G=0; c3 +21*w("2")-20*w("3")+1000*y("3")=G=0; c426*w("1")+9*w("2")+30*w("3")+1000*y("6")=G=0; c5 23*w("1")+9*w("2")+32*w("3")+1000*y("6")=G=0; c610*w("1")-28*w("2")+25*w("3")+1000*y("6")=G=0; c7 +3*w("2")-3*w("3")+1000*y("6")=G=0; c8 +3*w("2")-3*w("3")+1000*y("6")=G=0; c8 +3*w("2")-3*w("3")+1000*y("9")=L=0; c10 11*w("1")-30*w("2")+25*w("3")+1000*y("11")=L=0; c11 9*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; s0Vwe TezModeli /all/;</pre>		
<pre>c4 c5 c6 c7 c7 c8 c9 c10 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1")=3*w("3")=1000*y("1")=L=0; c2 = *w("1")=3*w("3")=1000*y("2")=G=0; c3 = + + + + + + + + + + + + + + + + +</pre>		
<pre>c6 c7 c8 c9 c10 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1")-3*w("3")-1000*y("1")=L=0; c2 = 6*w("1")+3*w("3")+1000*y("2")=G=0; c3 + 21*w("2")-20*w("3")+1000*y("3")+=G=0; c4 = 26*w("1")-11*w("2")+33*w("3")+1000*y("4")=G=0; c5 23*w("1")+9*w("2")-34*w("3")+1000*y("5")=G=0; c6 = 10*w("1")-28*w("2")+25*w("3")+1000*y("6")=G=0; c7 + 3*w("2")-8*w("3")+1000*y("6")=G=0; c8 + 3*w("2")-8*w("3")+1000*y("6")=C=0; c9 = 21*w("1")+20*w("2")+25*w("3")+1000*y("10")=L=0; c1 = 9*w("1")-34*w("2")+26*w("3")+1000*y("10")=L=0; c1 = 9*w("1")+25*w("2")-10*w("3")+1000*y("12")=C=0; c1 = 26*w("1")+25*w("2")-10*w("3")+1000*y("12")=C=0; c1 = 26*w("1")+25*w("2")-10*w("3")+25*w("2")-26*w("1)+25*w("2")+25*w("2")+25</pre>		
<pre>c7 c8 c9 c10 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1. 3*w("1")-3*w("3")-1000*y("1")=L=0; c2 8*w("1")+3*w("3")+1000*y("2")=G=0; c3. + 21*w("2")-20*w("3")+1000*y("3")=G=0; c4 26*w("1")-11*w("2")+30*w("3")+1000*y("4")=G=0; c5 23*w("1")+9*w("2")-34*w("3")+1000*y("5")=G=0; c610*w("1")+28*w("2")+25*w("3")+1000*y("6")=G=0; c7. + 3*w("2")-8*w("3")+1000*y("6")=G=0; c8. + 3*w("2")-8*w("3")+1000*y("8")=C=0; c9 21*w("1")+20*w("2")+25*w("3")+1000*y("10")=L=0; c10. 11*w("1")-34*w("2")+26*w("3")+1000*y("10")=L=0; c11. 9*w("1")+34*w("2")+23*w("3")+1000*y("12")=C=0; c12 28*w("1")+25*w("2")-10*w("3")+1000*y("12")=C=0; c12 28*w("1")+25*w("12")-10*w("12")+25*w("12")+25*w("12")+25*w("12"</pre>	L8 c5	
<pre>c8 c9 c10 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1. 3*w("1")-3*w("3")-1000*y("1")=L=0; c2 0*w("1")+3*w("3")+1000*y("2")=G=0; c3. + 21*w("2")-20*w("3")+1000*y("3")=G=0; c4 26*w("1")-11*w("2")+30*w("3")+1000*y("4")=G=0; c5. 23*w("1")+9*w("2")-34*w("3")+1000*y("6")=G=0; c6 10*w("1")-28*w("2")+25*w("3")+1000*y("6")=G=0; c7. + 3*w("2")-3*w("3")+1000*y("7")=G=0; c8. + 3*w("2")-3*w("3")+1000*y("7")=G=0; c9 21*w("1")+20*w("2")-1000*y("9")=L=0; c10. 11*w("1")-34*w("2")+26*w("3")+1000*y("10")=L=0; c11. 9*w("1")+25*w("2")-10*w("3")+1000*y("11")=G=0; c12 28*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
<pre>c9 c10 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1")-3*w("3")-1000*y("1")=L=0; c28*w("1")+3*w("3")+1000*y("2")=G=0; c3 +21*w("2")-20*w("3")+1000*y("3")=G=0; c426*w("1")-11*w("2")+30*w("3")+1000*y("4")=G=0; c5 23*w("1")+9*w("2")-34*w("3")+1000*y("5")=G=0; c610*w("1")-28*w("2")+25*w("3")+1000*y("6")=G=0; c7 +3*w("2")-3*w("3")+1000*y("8")=G=0; c8 +3*w("2")-8*w("3")+1000*y("8")=E=0; c921*w("1")+20*w("2")-1000*y("8")=L=0; c10 11*w("1")-30*w("2")+23*w("3")+1000*y("10")=L=0; c10 9*w("1")+25*w("2")+23*w("3")+1000*y("11")=G=0; c1228*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>	20 c7	
<pre>c10 c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1. 3*w("1")=3*w("3")=1000*y("1")=L=0; c28*w("1")+3*w("3")+1000*y("2")=G=0; c3. +21*w("2")=20*w("3")+1000*y("3")=G=0; c426*w("1")=11*w("2")=13*w("3")+1000*y("4")=G=0; c5. 23*w("1")+9*w("2")=23*w("3")+1000*y("5")=G=0; c610*w("1")=28*w("2")+25*w("3")+1000*y("6")=G=0; c7. +3*w("2")=3*w("3")+1000*y("6")=G=0; c8. +3*w("2")=8*w("3")+1000*y("8")=C=0; c921*w("1")+20*w("2")+20*w("3")+1000*y("10")=L=0; c10. 11*w("1")=34*w("2")+23*w("3")+1000*y("10")=C=0; c1228*w("1")+25*w("2")-10*w("3")+1000*y("12")=C=0; c1228*w("1")+25*w("10")+25*w("10")+25*w("10")+25*w("10")+</pre>		
<pre>c11 c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1)-3*w("3")=1000*y("1")=L=0; c2 = 8*w("1")+3*w("3")+1000*y("2")=G=0; c3 ±21*w("2")-20*w("3")+1000*y("3")=G=0; c4 = 26*w("1")-11*w("2")+30*w("3")+1000*y("4")=G=0; c5 23*w("1")+9*w("2")+23*w("3")+1000*y("5")=G=0; c6 = 10*w("1")-28*w("2")+25*w("3")+1000*y("6")=G=0; c7 ±3*w("2")-3*w("3")+1000*y("7")=G=0; c8 ±3*w("2")-8*w("3")+1000*y("7")=G=0; c9 = 21*w("1")+20*w("2")+1000*y("10")=L=0; c10 11*w("1")-30*w("2")+23*w("3")+1000*y("10")=L=0; c11 9*w("1")+25*w("2")-10*w("3")+1000*y("11")=G=0; c1228*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
<pre>c12; obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1")-3*w("3")-1000*y("1")=L=0; c28*w("1")+3*w("3")+1000*y("2")=G=0; c3 +21*w("2")-20*w("3")+1000*y("3")=G=0; c426*w("1")-11*w("2")+30*w("3")+1000*y("4")=G=0; c5 23*w("1")+9*w("2")-34*w("3")+1000*y("6")=G=0; c610*w("1")-28*w("2")+25*w("3")+1000*y("6")=G=0; c7 +3*w("2")-3*w("3")+1000*y("7")=G=0; c8 +3*w("2")-8*w("3")+1000*y("7")=G=0; c921*w("1")+20*w("2")-1000*y("8")=G=0; c10 11*w("1")-30*w("2")+26*w("3")+1000*y("10")=L=0; c11 9*w("1")+25*w("2")+23*w("3")+1000*y("11")=G=0; c1228*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
<pre>obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1")-3*w("3")-1000*y("1")=L=0; c28*w("1")+3*w("3")+1000*y("2")=G=0; c3 +21*w("2")-20*w("3")+1000*y("3")=G=0; c426*w("1")-11*w("2")+30*w("3")+1000*y("4")=G=0; c5 23*w("1")+9*w("2")-34*w("3")+1000*y("5")=G=0; c610*w("1")-28*w("2")+25*w("3")+1000*y("6")=G=0; c7 +3*w("2")-8*w("3")+1000*y("8")=G=0; c8 +3*w("2")-8*w("3")+1000*y("8")=L=0; c10 11*w("1")+20*w("2")+26*w("3")+1000*y("10")=L=0; c10 11*w("1")+25*w("2")+26*w("3")+1000*y("11")=G=0; c1228*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
<pre>obj z=E=sum(i,y(i));; c0 sum(j,w(j))=E=1; c1 3*w("1")-3*w("3")-1000*y("1")=L=0; c28*w("1")+3*w("3")+1000*y("2")=G=0; c3 +21*w("2")-20*w("3")+1000*y("4")=G=0; c426*w("1")-11*w("2")+30*w("3")+1000*y("4")=G=0; c5 23*w("1")+9*w("2")+23*w("3")+1000*y("5")=G=0; c610*w("1")-28*w("2")+25*w("3")+1000*y("5")=G=0; c7 +3*w("2")-3*w("3")+1000*y("7")=G=0; c8 +3*w("2")-8*w("3")+1000*y("8")=G=0; c921*w("1")+20*w("2")+25*w("3")+1000*y("10")=L=0; c10 11*w("1")-30*w("2")+23*w("3")+1000*y("11")=G=0; c11 9*w("1")+34*w("2")+23*w("3")+1000*y("12")=G=0; c1228*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
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<pre>c7 +3*w("2")-3*w("3")+1000*y("7")=G=0; c8 +3*w("2")-8*w("3")+1000*y("8")=G=0; c921*w("1")+20*w("2")-1000*y("9")=L=0; c10 11*w("1")-30*w("2")+26*w("3")-1000*y("10")=L=0; c11 9*w("1")-34*w("2")+23*w("3")+1000*y("11")=G=0; c1228*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
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<pre>c11 9*w("1")-34*w("2")+23*w("3")+1000*y("11")=G=0; c1228*w("1")+25*w("2")-10*w("3")+1000*y("12")=G=0; model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
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<pre>model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
<pre>model TezModeli /all/; solve TezModeli using MIP min z;</pre>		
solve TezModeli using MIP min z;		
	<pre>3 solve TezModeli using MIP min z; 4 display w.L, z.L, y.L;</pre>	

Figure 6. Screenshot of Gams.

### 3.3.2 The Mathematical Model for MR-Sort

We aim to find a set of MR-Sort parameters that can explain the preferences of the DM. The parameters of the MR-Sort are class boundaries, criteria weights and the cut level. We define these parameters as the decision variables of the mathematical model. The class assignments of the suppliers are also decision variables. If the DM prefers supplier A to supplier B, we impose a constraint stating that the class of supplier A is at least as good as supplier B. The model counts the number of suppliers assigned to each class and the objective function is to maximize the cardinality of the class that has the least number of suppliers. If the optimal objective function value is 0 then there is a class without any alternatives assigned to it. In such a case we conclude that the preferences of the DM cannot be explained with the MR-Sort model. We use the MR-Sort GAMS code implemented by Özpeynirci, Özpeynirci, and Mousseau (2020).

## **CHAPTER 4: SURVEY DESIGN**

In a system using three criteria for supplier selection, we conduct an anonymous online survey with DMs. This survey study consists of 3 parts. The purpose of this survey study is to find the evaluation method in the minds of the survey participants, namely the DMs. In the first part, we ask questions about the professional status of the survey participants. These questions are about the activity field of the company they work for, their position in the company, and the experience in their position. We create multiple-choice questions. The purpose of asking these questions is to get an idea of our survey participants. We aim to avoid questions that participants would hesitate to respond to. In the second part, we ask each DM to choose 3 most important criteria for supplier selection among a list of 14 criteria based on their own experience. We compile the list of 14 multiple choice supplier selection criteria from the studies of Dicson (1992), Weber (1991), and Ho, Xu, and Dey (2020). Thus, we aim to reveal which supplier selection criteria are more important in the minds of each DM. Finally, we ask a total of 12 comparative questions, given performance values, in a three-criteria system. Each participant (DM) determines what these three criteria are. The first criterion is the criterion that the DM finds most important. Afterwards, the second and third important criteria follow, respectively. Suppliers' performance is rated from 0 (worst) to 100 (best) for all three criteria. We cover 12 questions in more detail in Section 4.1. We ask each participant a total of 16 questions under three sections.

We first conduct our survey study with people from academia for trial purposes. During this trial period, it became clear that there are some problems with the wording of the questions, and we rearranged the questionnaire accordingly. After the editing, we share the survey with these people again. As a result of the last feedback we received from people in the academy, we updated our survey for the last time and made it operational. As a result of all this, we start working on filling this online anonymous survey with real DMs.

A total of 55 DMs participate in our survey study. We conduct our online anonymous survey among employees and executives of companies in decision-making positions

such as senior management, procurement, supply chain management, etc. We take care to select our survey participants from people familiar with mathematical models, albeit simple ones. We share our survey with the participants via e-mail and similar tools. We keep our online anonymous survey open for a total of 7 days. Our participants fill out this survey at their own convenient time. At the end of the 7th day, we turn off accepting responses to our survey study. We gather our survey data in the spring of 2021.

#### 4.1 Question Design

In a system where three criteria are used in supplier selection, we ask the DM a total of 12 pairwise comparative questions. The DM themselves determine what these three criteria are . The first criterion is the criterion that the DM finds most important. Afterward, the second and third important criteria come, respectively. The performance scores of all suppliers are evaluated between 0 (worst) and 100 (best) for all three criteria. In each criterion, a higher value is preferable. For each pairwise comparison, we ask the DM which supplier she or he prefers. For example: "The first criterion corresponds to the most important criteria for you, the second criterion is moderately important and the third criterion corresponds to the least important criteria. Which supplier do you prefer: A (21, 47, 82) or B (24, 47, 79)? A and B here represent the two separate suppliers that we are being compared against each other.

Alternative Suppliers	Most important criteria	Moderately important criteria	Least important criteria
А	21	47	82
В	24	47	79

Table 2. Pairwise Comparison.

We prepare all comparative questions according to the binary tree structure (see Figure 9. for an example). After each choice made by the DM, the next question is asked, taking into account the choice made by the DM.

For example, if the DM chooses supplier A against B in the first question, the following comparison question comes up as the second question; C (12, 46, 90) or D (20, 46, 87)? However, if the DM chooses supplier B against A in the first question, the following comparison question comes up as the second question; E (48, 13, 85) or F (48, 34, 65)? After each decision made by the DM, the next pairwise comparison question is presented using the designed tree. In this way, we ask the DM a total of 12 questions. While preparing these 12 questions, we structure the 5<sup>th</sup>, 6<sup>th</sup>, 11<sup>th</sup>, and 12<sup>th</sup> questions in a way that would guide the DM to tricky options. The purpose of creating this discrepancy is to show that DMs can give inconsistent answers when they choose with a linear value function. Korhonen et al. (2012) reveal that people cannot make decisions consistent with a linear value function when making various choices. According to them, when people choose with a linear value function, they do not pay enough attention to their choices. They point out that it is very difficult for DMs to be completely consistent with a decision rule and that DMs can make mistakes. In addition, they think that DMs can change their minds.

In this study, we claim that we may encounter situations where we cannot explain the preferences of DMs with a linear value function in real life. We claim that the MR-Sort method, as a non-compensatory method to overcome such a situation, eliminates this problem. For these reasons, we add tricky questions to which DMs could give inconsistent answers to the 12 comparative questions.

We structure the first four questions in such a way that no matter which options the DM chooses, she or he can give consistent answers with a linear value function. In the 5<sup>th</sup> and 6<sup>th</sup> questions, we ask tricky questions. In Figure 7. we are talking about an example of the weight space of these tricky questions. For example, suppose a DM has a weight space as in Figure 7. as a result of the decisions made in the first four questions. In question 4, we ask the DM whether you would prefer supplier A or supplier B. If the DM chooses supplier A, our new weight space is contained within a quadrilateral area. If the DM chooses supplier B, our new weight space is a triangle.

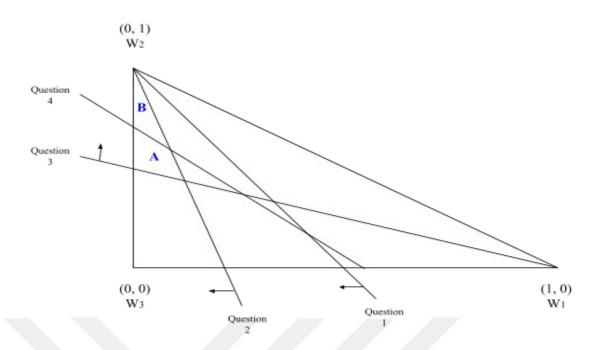


Figure 7. Pairwise Comparison Examples.

Consider that the DM preferences supplier A. In such a case, our new weight space is contained within a quadrilateral area. We show this new field with the curved connector in Figure 8.

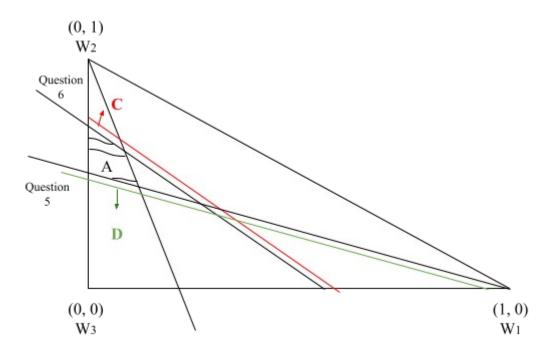


Figure 8. Pairwise Comparison Examples.

Until now, we can explain all the answers given by the DM to these four questions with the linear value function. While preparing questions 5 and 6, we chose two line segments very close to this quadrilateral. In Figure 8., we show the line segments with green and red colors. Let's assume that the green line represents the weights where the utilities of supplier A and D are equal. If I ask DM to compare supplier A and supplier D in question 5, the DM may prefer supplier D; in such a case, we conclude that we cannot explain the preference of this DM with the linear value function. We apply the same strategy in question 6 as well using Supplier C. If the DM prefers supplier A in questions 5 and 6, we conclude that we do not have enough evidence to claim the preferences of this DM cannot be explained by the linear value function. While preparing these questions, we aim to obtain situations that cannot be explained by the linear value function of the DMs' preferences.

In the first 6 questions, we evaluate the suppliers on 3 criteria between 0 (worst) and 100(best) points. In the second 6 questions, we prepare the scores obtained from 3 criteria in the first 6 questions by changing their places. For example, let's show the scores obtained by the supplier group in the first 6 questions as follows; (X, Y, Z). In the second 6 questions, we change the places of these scores as follows; (Y, Z, X). In this way, we ask a total of 12 pairwise comparative questions to the DMs in this survey study. We prepared these 12 questions with the binary data structure.

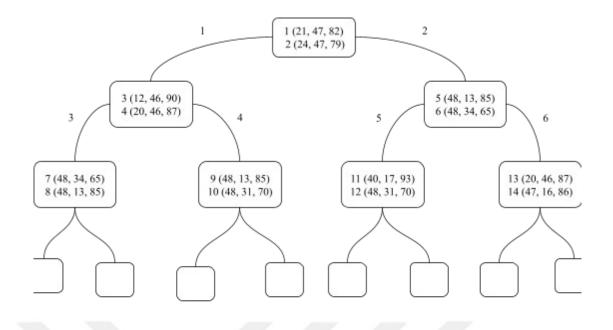


Figure 9. Tree Structure First 6 Questions.

Consider Figure 9., we start by asking our survey participant this question first; do you prefer the  $1^{st}$  supplier with scores of (21, 47, 82) or the  $2^{nd}$  supplier with scores of (24, 47, 79)? While providing her or his preference, the DM knows that the  $1^{st}$  criterion is the most important for her, followed by the  $2^{nd}$  and  $3^{rd}$  criteria. Since we create the questions according to the binary tree structure, the next question is formed based on the previous responses of the DM. If the DM prefers the  $1^{st}$  supplier, in the next question we ask the DM whether she or he prefers the  $4^{th}$  or  $5^{th}$  supplier. If the DM prefers the  $7^{th}$  or  $8^{th}$  supplier, in the next question we ask the DM whether she or he prefers the  $7^{th}$  or  $8^{th}$  supplier. Then, in line with this second choice, the third question comes before them. In this way, we prepare a total of 12 questions, but we explain these 12 questions to you in two separate parts. In this way, we prepare a total of 6 questions that we could ask the DM in the first part. In the next paragraph, we explain how we create the second 6 questions in Figure 10.

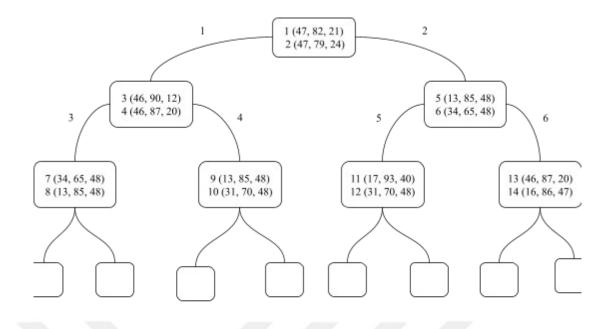


Figure 10. Tree Structure Second 6 Questions.

In Figure 4.1.5, we prepare questions 7 to 12 by replacing the scores from 3 criteria in the first 6 questions. In our first question, the performance values of the two suppliers are as follows; 1 (21, 47, 82) and 2 (24, 47, 79). While creating our<sup>7 th</sup> question, we put the first of these performance values at the end. In question<sup>7 th</sup>, the DM evaluates the <sup>1t</sup> and 2<sup>nd</sup> suppliers with the following performance values; 1 (47, 82, 21) and 2 (47, 79, 21). In this way, we prepare the questions from 7 to 12 by updating all the questions we create in the first 6 questions. In this way, we prepare a question pool of 204 questions in total. In our survey study, the DM only answers 12 questions from a pool of 204 questions.

### 4.2 Alternative Supplier List

In this survey study, the number of suppliers we ask the DMs using the pairwise comparison method is 60 in total. We have performance values of these 60 suppliers based on 3 criteria. We ask the DM to prefer between them by comparing 2 suppliers from this set of alternative suppliers. Our aim here is to measure whether DMs can make consistent decisions with the linear value function, which is a compensatory method. For DMs who cannot make preferences consistent with the linear value

function, we examine whether we can explain their preferences with the MR-Sort method, which is a non-compensatory method. In Table 3., we share the performance values of a set of 60 suppliers, based on 3 criteria.

In the survey, there are a total of 60 suppliers and 204 pairwise comparison questions prepared on a tree structure using these suppliers. Each participant follows a path from the root of the tree to one of the leaves and answers 12 questions. Each response of the participant affects the path she follows.

Alternatives suppliers	The score for the first criterion (most important)	The score for the second criterion (moderately important)	The score for the third criterion (less important)
1	20	46	87
2	50	45	68
3	24	45	80
4	40	17	93
5	34	19	97
6	12	46	90
7	22	20	100
8	45	55	69
9	24	47	79
10	48	34	65
11	35	63	76
12	20	32	98
13	21	47	82
14	48	31	70
15	46	32	72
16	25	25	99
17	29	28	95

Table 3. Supplier Performance Values.

18	47	30	85
19	48	13	85
20	47	16	86
21	30	85	20
22	35	18	97
23	48	29	70
24	45	16	87
25	46	51	54
26	31	18	97
27	33	10	98
28	44	17	92
29	14	31	98
30	41	17	93
31	46	87	20
32	45	68	50
33	45	80	24
34	17	93	40
35	10	97	34
	19	57	54
36	19 46	90	12
36 37			
	46	90	12
37	46 20	90 100	12 22
37 38	46 20 55	90 100 69	12 22 45
37 38 39	46 20 55 47	90 100 69 79	12 22 45 24
37 38 39 40	46 20 55 47 34	90 100 69 79 65	12 22 45 24 48
37 38 39 40 41	46 20 55 47 34 63	90 100 69 79 65 76	12 22 45 24 48 35
37 38 39 40 41 42	46 20 55 47 34 63 32	90 100 69 79 65 76 98	12 22 45 24 48 35 20
37 38 39 40 41 42 43	46 20 55 47 34 63 32 47	90 100 69 79 65 76 98 82	12 22 45 24 48 35 20 21
37 38 39 40 41 42 43 43 44	46 20 55 47 34 63 32 47 31	90 100 69 79 65 76 98 82 70	12 22 45 24 48 35 20 21 48

48	30	85	47
49	13	85	48
50	16	86	47
51	85	20	30
52	18	97	35
53	29	70	48
54	16	87	45
55	51	54	46
56	18	97	31
57	10	98	33
58	17	92	44
59	31	98	14
60	17	93	41

Figure 11. shows the weight space decomposition for the weighted total utility value of 60 suppliers. Each colored region represents the weight set for a supplier that has the highest utility value in the corresponding region.



Figure 11. Decomposition.

## 4.3 Application of Survey

We prepare our survey using Google's free, web-based Google Docs Editors package. We share this survey with the participants via e-mail and other social media tools. We explain the purpose of our survey to each participant shortly and clearly. Each participant contributed to our survey at their own available time. We keep our survey anonymous to encourage our survey participants to participate in the survey, and we try to keep our questions as simple and plain as possible. We keep our online anonymous survey open for a total of 7 days. At the end of the 7<sup>th</sup> day, we turn off accepting responses to our survey study.

# **CHAPTER 5: SURVEY RESULTS**

In this chapter, we share the results of the anonymous survey with 55 survey participants. We present the results under 3 headings. First, we report the general responses of the survey participants. This section is the part that provides a general idea about DMs. Second, we examine whether DMs' pairwise comparison decisions are consistent with a linear value function. Third, we examine whether we can explain the preferences of DMs that cannot be explained by a linear value function using the MR-Sort method.

### 5.1 General Responses

This section reports the first part of the survey questions. We show the sector, position and experience distribution of the participants. Next, we present the most important criteria for the participants.

Table 4. shows the fields of activity of the companies that our 55 survey participants work for. The sectoral distribution of 55 survey participants is as follows; 6 participants work in the plastic and rubber industry, 5 in the iron-steel industry, 4 in the chemical industry, 4 in the food industry, 4 in the health service, 4 in logistics.

Number of participants	Sectors	
6	Plastic and Rubber	
5	Iron and Steel	
4	Chemistry	
4	Food	
4	Health Service	
4	Logistics	
3	Clothing and Fashion	
3	Machinery and Equipment	
2	Construction	
2	Electrical Supplies	
2	Energy	
2	Packaging	
2	Steel Door Manufacturing	
2	Work Supplies and Equipment	
1	Automotive	
1	Clean Room Ventilation Systems	
1	Durable Goods	
1	Glassware Industry	
1	Home Textile	
1	Industrial Automation	
1	Mining Industry	
1	Retail	
1	Textile	
1	Tobacco Industry	

Table 4. Sectoral Distribution of Survey Participants.

Table 5. shows the positions of our 55 survey participants in the company they work for. Of the respondents, 14 are senior management, 12 are purchasing, 8 are sales and marketing, 8 are supply chain management.

Number of participants	Positions	
14	Senior Management	
12	Purchasing	
8	Sales and marketing	
8	Supply Chain Management	
4	Quality Control Management	
2	Production management	
2	Warehouse Management	
1	Coordinator	
1	Human Resources	
1	Planning	
1 Research and Developm		
1	Shipping and Receiving	

Table 5. Positions of Survey Participants (DMs).

We share the working years of our survey participants in their positions in Table 6. The majority of our survey participants have been working in their current positions for 1 to 5 years. The full years related to the subject are given in table 6.

Years	Number of participants
0 to 1	9
1 to 5	28
5 to 10	8
10 to 15	5
15 to 20	5
20 and more	0

Table 6. Working Years.

While we are conducting our survey with these 55 DMs, we ask each of our survey participants what the 3 most important supplier selection criteria are according to them. 94% of the participants believe that quality is one of the 3 most important criteria. After that, they believe that the price with 84% and the delivery with 51% are among the 3 most important criteria. The data we obtained from the survey are compatible with the data we obtained from the literature review. In Table 7., we show 55 DM's answers to the question of what the 3 most important supplier selection criteria are.

Criteria	Number of participants	Percentage (%)
Quality	50	91
Price	46	84
Delivery	28	51
Service	10	18
Relationship	8	15
Research and Development	5	9
Safety and Environment	4	7
Management	3	5
Reputation	3	5
Flexibility	2	4
Finance	2	4
Production Ability	2	4
Technology	1	2
Risk	1	2

Table 7. Supplier Selection Criteria.

### 5.2 Linear Value Function Consistency

We analyze the responses of each participant one by one. We aim to fit a linear value function that explains the preferences of the participant. We solve a mathematical programming model for each participant. Recall that, the model reports the minimum number of responses to be deleted so that the preferences of the DM can be expressed via a linear value function. For 12 participants, the model returns 0 as the optimal objective function value, indicating that their preferences are consistent. We observe different levels of inconsistencies in the remaining 43 participants' responses. For one participant, 5 responses should be removed, which is the highest value we encounter. Table 8. reports the model results. Based on these, only 22% of the

DMs preferences can be expressed via a linear value function, and the remaining 78% requires a more complex method that can handle their preferences.

Number of participants	Numbers of inconsistent preferences
12	0
17	1
15	2
6	3
4	4
1	5

Table 8. Number of Inconsistent Preferences.

The DM's preference, which is explained by the linear value function within the data we obtained from the survey, is as follows. We ask the DM, which supplier do you prefer; 13 (21 - 47 - 82) or 9 (24 - 47 - 79)? The DM prefers 9<sup>th</sup> supplier. In the second question, we compare these two suppliers; which supplier do you prefer; 19 (48 - 13 - 85) or 10 (48 - 34 - 65)? The DM prefers  $10^{th}$  supplier. In the third question, we ask the DM, which supplier do you prefer; 1 (20 - 46 - 87) or 20 (47 -16 - 86)? The DM prefers 20<sup>th</sup> supplier. In the fourth question, we ask the DM, which supplier do you prefer; 9 (24 - 47 - 79) or 17 (29 - 28 - 95)? The DM prefers 9<sup>*th*</sup> supplier. In the fifth question, we ask the DM, which supplier do you prefer; 6 (12 - 46 - 90) or 4 (40 - 17 - 93)? The DM prefers  $4^{th}$  supplier. In the sixth question, we ask the DM, which supplier do you prefer; 20 (47 - 16 - 86) 15 (46 - 32 - 72)? The DM prefers 15<sup>th</sup> supplier. In the seventh question, we ask the DM, which supplier do vou prefer; 43 (47 - 82 - 21) or 39 (47 - 79 - 24)? The DM prefers 43<sup>th</sup> supplier. In the eighth question, we ask the DM, which supplier do you prefer; 36 (46 - 90 - 12) or 31 (68 - 87 - 20)? The DM prefers 31<sup>th</sup> supplier. In the ninth question, we ask the DM, which supplier do you prefer; 49 (13 - 85 - 48) or 44 (31 - 70 - 48)? The DM prefers 44<sup>th</sup> supplier. In the tenth question, we ask the DM, which supplier do you prefer; 45 (32 - 72 - 46) or 46 (25 - 99 - 25)? The DM prefers 45<sup>th</sup> supplier. In the

eleventh question, we ask the DM, which supplier do you prefer; 37 (20 - 100 - 22)

or 44 (31 - 70 - 48)? The DM prefers <sup>44 th</sup> supplier. Finally, in the last question, we ask the DM, which supplier do you prefer; 50 (16 - 86 - 47) or 60 (17 - 93 - 40)? The  $50_{th}$ 

DM prefers "" supplier. We analyze whether the preferences of the DM who makes these preferences can be explained by the linear value function. As a result, we find that we can explain the preferences of the DM who made these preferences with the linear value function. We say that there is no inconsistency in the preferences of this DM. When we examined the preferences of another DM, we find that he or she made the same preferences as this DM in the first 11 questions. However, by choosing the 60 supplier in the twelfth question, he or she makes a preference that cannot be explained by the linear value function. In such a case, we say that we cannot explain the preference of this DM with the linear value function. We can say that this DM chooses only one inconsistent preference. 12 out of 55 DMs choose at different levels inconsistent that are not consistent with the linear value function.

### 5.3 MR-Sort Consistency

We reconsider the preferences of these 55 DMs with a non-compensatory method, MR-Sort. We use the mathematical model presented in Mousseau, Özpeynirci, and Özpeynirci (2018). Similar to Section 5.2, we solve the model for each participant one by one.

Some suppliers are used in multiple questions and the number of distinct suppliers used in 12 pairwise questions varies between 18 to 24. The mathematical model aims to assign these distinct suppliers in such a way that the minimum number of suppliers in a class is maximum while considering the preferences of the DM. For each participant, the model is capable of splitting suppliers into three classes in a balanced way. For instances with 18, 19 or 20 distinct suppliers, we observe at least 6 suppliers in each class. For instances with higher numbers of distinct suppliers, we observe at least 7 suppliers in each class. We conclude that MR-Sort, a noncompensatory method, is successful in expressing the preferences of a DM, those can not be expressed with a linear value function.

# **CHAPTER 6: CONCLUSION**

In this thesis, we examine the supplier selection problem, the methods proposed for solving the problem and the criteria used in various methods. In the early years of working on the supplier selection problem, individual methods are frequently used because of their ease of use. However, individual methods are often criticized for not being good at predicting unknown points. When we look at the literature published on the supplier selection problem in the last decade, we see that integrated methods are frequently used. Integrated methods used on the supplier selection problem contribute to predicting unknown points and making healthier decisions. On the other hand, as a result of the literature review and survey study, the 3 most important supplier selection criteria that maintain their importance today are quality, price, and delivery. While examining the methods, we realize that the proposed methods are compensatory methods. We believe that compensatory methods may not be enough in some cases in the supplier selection problem.

To prove this claim, we prepare an online anonymous survey based on pairwise comparisons in which specially designed suppliers are evaluated according to three criteria. The survey presents pairwise comparison questions to the participant one by one, and the participant's answers affect the next question to be asked, each participant provides his/her preferences by responding12 pairwise comparison questions. A total of 55 DMs who are active in business life filled out this survey. For each participant of the survey, we check the consistency of the responses using two different mixed integer programming models; the former model assumes the supplier selection method is a compensatory method based on a linear value function, and the latter assumes the use of MR-Sort, a non-compensatory method. The main research question in this thesis is to analyze the responses of a DM expressing his preferences using a compensatory method in the supplier selection problem.

The survey results indicate that only 12 out of 55 participants consistently explained their preferences with a linear value function. The preferences of the remaining 43

DMs can not be explained by a linear value function. These results show us that there is also a need for non-compensatory methods in the literature. To fill this gap, we examine the survey results with a non-compensatory method. We test whether MR-Sort, a non-compensatory method, can explain the DMs' preferences. The MR-Sort is sufficient to explain the preference of all DMs.

As a result of the survey study, it is revealed that a linear value function is not sufficient to explain the preferences of the DMs on the supplier selection problem. Managers use more complex methods when making their decisions. However, the methods used in the supplier selection problem in the literature are designed for simpler decision-making situations. For this reason, more complex decision-making methods are needed in the literature. We used the MR-Sort, which is a non-compensatory method, in the thesis. As a result, MR-Sort consistently explained the preferences of the DMs.

Our survey results show that use of a noncompensatory method may better explain the preferences of the DMs for the supplier selection problem. We have two future directions. The first one, we believe that using MR-sort in a real life application is a possible future research direction. Another future research direction is to adapt other non-compensatory methods for the supplier selection problem.

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