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A CUSTOMER-ORIENTED CHOICE MODEL: THE INTEGRATION OF DISCRETE CHOICE EXPERIMENT AND KANSEI ENGINEERING

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I hereby declare that this master’s thesis titled as “A Customer Oriented Choice Model: The Integration of Discrete Choice Experiment and Kansei Engineering” has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

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ABSTRACT

Master's Thesis

A Customer-Oriented Choice Model: The Integration of Discrete Choice Experiment and Kansei Engineering

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In today's age of technology and rapidly continuing globalization, consumers have become even more conscious and selective in their product choices. By taking advantage of the internet, people can see where the product is cheapest, learn the positive and negative aspects of the, and find another product alternative that satisfies the same need. Besides, designing products based on the product features and people's feelings is having of great importance for manufacturers to gain advantage at the market. In this regard, the studies of consumer behavior accelerated, and many new methods has emerged in this field.

One of these methods, the Discrete Choice Experiment (DCE) uses design and analysis of experiments to reveal consumers' preferences on products and services. Another method, Kansei Engineering transfers people's psychological feelings and images to the product design process.

In this study, a customer-oriented choice model reinforced by the integration of Kansei engineering and DCE is proposed. The aim of this model is to determine both product attributes and perceptions and feelings about the product. With the proposed model, both the product alternative that maximizes the customers' utility and the perceptions and feelings of customers are revealed. Unlike studies in similar context, it is planned to obtain results that are closer to the actual choice behaviors, since people directly choose from the alternatives offered instead of ranking or rating the product alternatives.

In the model, firstly product attributes and Kansei words are collected by the help of subject matter experts/designers. Then, two consecutive experiments are designed. In the first experiment, customers are asked to

choose their most preferred alternatives among hypothetical products created with the determined attribute. The data are analyzed using several discrete choice methods and accordingly, the alternative maximizes both the utility of the customers and the attributes' part-worth utilities is revealed. Next, the product alternatives created based on product attributes are presented to the customers in the Kansei Engineering Experiment. This time, to reveal the feeling and perceptions that the alternatives arouse in customers, the product alternatives are evaluated by the Kansei words. By using suitable quantitative methods, the words that define the products are revealed. At the end of two experiments, the attributes and feeling/perceptions of consumer-oriented product are elicited.

The model was applied in designing a university course. At the end of the DCE, it was revealed that the students attach importance to the attributes that express how the examination is handled, and the problem-solving session will be held, and who will determine their groups for the term project. In addition, a course alternative that maximizes student utility has been generated. Then, after the KEE the relationship between course attributes and Kansei words is shown.

This study contributes to the literature by presenting a choice model enhanced by the integration of DCE and Kansei Engineering. This model is an effective model that can be used in modeling the choices of all existing or non-existent products and services, and it simultaneously evaluates product attributes and customers' feelings and perceptions about the product.

Keywords: Choice Modelling, Discrete Choice Experiments, Kansei Engineering, Product Design

ÖZET

Yüksek Lisans Tezi

Müşteri Odaklı Seçim Modeli: Ayrık Seçim Deneyi ile Kansei Mühendisliğinin Bütünleşimi

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Günümüz teknoloji çağında ve hızla devam eden küreselleşmede tüketiciler ürün seçimlerinde daha da bilinçli ve seçici hale gelmiştir. İnternetin tüm nimetlerinden yararlanarak insanlar birkaç dakika içerisinde fiyat karşılaştırması yapan siteleri kullanarak ürünün en ucuz nerede olduğunu görebilir, kullanıcı yorumlarını okuyarak ürünün olumlu ve olumsuz yönlerini öğrenebilir, aynı ihtiyacı karşılayan başka bir ürün alternatifi bulabilir. Ayrıca, hem müşterilerin önemsediği ürün özellikleri hem de müşterilerin o ürüne ilişkin algı ve hislerine dayalı değerlendirmelere göre ürün tasarlamak, üreticilerin pazarda avantaj sağlamaları açısından büyük önem taşımaktadır. Bu bağlamda tüketici davranışı çalışmaları hızlanmış ve bu alanda birçok yeni yöntem ortaya çıkmıştır.

Bu çalışmanın amacı, Kansei Mühendisliği ve Ayrık Seçim Deneyinin bütünleşimi ile güçlendirilmiş bir müşteri odaklı bir seçim modeli önermektir. Bu bağlamda önerilen model ile hem tüketicilerin faydasını enbüyükleyen ürün alternatifi hem de tüketicilerin bu alternatife ilişkin algı ve duyguları ortaya çıkarılacaktır.

Bu çalışmada, Kansei Mühendisliği ve Kesikli Seçim Deneyinin bütünleşimi ile güçlendirilmiş müşteri odaklı bir seçim modeli önerilmiştir. Bu modelin amacı, hem ürün özelliklerini hem de ürünle ilgili algı ve duyguları belirlemektir. Önerilen model ile hem müşterilerin faydasını enbüyükleyen ürün alternatifi hem de müşterilerin bu alternatife ilişkin algıları ve duyguları ortaya çıkarılmıştır. Benzer bağlamdaki çalışmalardan farklı olarak, müşteriler ürün alternatiflerini sıralamak veya derecelendirmek yerine doğrudan kendilerine

sunulan alternatifler arasından seçim yaptıkları için gerçek seçim davranışlarına daha yakın sonuçlar elde edilmesi planlanmaktadır.

Önerilen modelin aşamalarına bağlı olarak, konu uzmanları/tasarımcıları yardımıyla öncelikle ürün özellikleri ve Kansei kelimeleri toplanır. Daha sonra iki ardışık deney tasarlanmıştır. İlk deneyde, müşterilerden belirlenen nitelik ile oluşturulan varsayımsal ürünler arasından en çok tercih ettikleri alternatifi seçmeleri istenir. Deneysel veriler, çeşitli ayrık seçim analiz yöntemleri kullanılarak analiz edilir ve buna göre, hem müşterilerin faydasını hem de özniteliklerin kısmi-değerli faydalarını maksimize eden alternatif ortaya çıkar. Ardından, ürün özellikleri kullanılarak oluşturulan ürün alternatifleri ikinci deneyde müşterilere sunulmaktadır. Bu kez alternatiflerin müşterilerde uyandırdığı duygu ve algıları ortaya çıkarmak için, ürün alternatifleri Semantik Diferansiyel Ölçeğinden çıkarılan Kansei kelimeleri ile değerlendirilir. Çalışmanın niteliğine, uzmanın bilgisine ve günün koşullarına bağlı olarak veri analizine uygun nicel yöntemler belirlenir ve bu yöntemler kullanılarak ürünleri tanımlayan kelimeler ortaya çıkarılıt. Bu iki ardışık deneyin sonunda, müşteri odaklı ürünün özellikleri ve müşterilerin hissi/algıları ortaya çıkarılmaktadır.

Bu çalışmada önerilen model bir dersin yeniden tasarım sürecinde uygulanmıştır. Dersin iki ve üç düzeyli sekiz özelliği ile gerçekleştirilen Ayrık Seçim Deneyi sonunda öğrencilerin en çok hangi sınavların yapılacağı, soru çözüm oturumunun nasıl gerçekleştirileceği ve dönem projesi için gruplarının kim tarafından belirleneceğini ifade eden özelliklere önem verdiği ortaya çıkmış ve öğrenci faydasını enbüyükleyen ders alternatifi oluşturulmuştur. Ardından Kansei Mühendisliği Deneyi gerçekleştirilmiş ve kullanılan Kansei kelimelerinin gruplandırılması yapılmıştır. Son olarak ders özellikleri ile Kansei kelimeleri arasındaki ilişki gösterilmiştir.

Bu çalışma Kesikli Seçim Deneyi ile Kansei Mühendisliğinin bütünleşimi ile güçlendirilmiş bir seçim modeli sunması ile literatüre katkı sağlamaktadır. Bu modelin var olan ya da olmayan tüm ürün ve hizmetlerin seçimlerinin modellenmesinde kullanılabilecek etkili bir model olması ve ürün özellikleri ile müşterilerin ürüne beslediği his ve algılarını aynı anda değerlendirmesi modelin en önemli özellikleridir.

Anahtar Kelimeler: Ayrık Seçim Deneyi, Kesikli Seçim Deneyi, Kansei Mühendisliği, Seçim Modelleme, Ürün Tasarımı

A CUSTOMER-ORIENTED CHOICE MODEL: THE INTEGRATION OF DISCRETE CHOICE EXPERIMENT AND KANSEI ENGINEERING

CONTENTS

CHAPTER TWO

KANSEI ENGINEERING

CHAPTER THREE

METHODOLOGY

ABBREVIATIONS

CA	Conjoint Analysis
CBC	Choice Based Conjoint
DCA	Discrete Choice Analysis
DCE	Discrete Choice Experiment
DCEs	Discrete Choice Experiments
FA	Factor Analysis
FDs	Factorial Designs
FFDs	Fractional Factorial Designs
HB	Hierarchical Bayes
HBE	Hierarchical Bayesian Estimation
HKES	Hybrid Kansei Engineering System
KE	Kansei Engineering
KEE	Kansei Engineering Experiment
KES	Kansei Engineering System
KMO	Kaiser-Meyer-Olkin
KW	Kansei Words
MH	Metropolis-Hasting
MU	Marginal Utility
QFD	Quality Function Deployment
QMT	Quantitative Methods
QT1	Quantification Theory Type I
QT3	Quantification Theory Type III
PC	Principal Component
PCA	Principal Component Analysis
PLS	Partial Least Square Regression
PoS	Point of Sales
RUM	Random Utility Model
RUT	Random Utility Theory
SD	Semantic Differential
TU	Total Utility
U	Utility
VKES	Virtual Kansei Engineering System

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INTRODUCTION

With the internet and developing technology, the borders of the world have disappeared, and the world has become a global village (McLuhan, 1967: 272). In this unlimited world, consumers have become very conscious and rigorous while making a product choice. It is no longer enough for them to just need a product to buy. By taking advantage of all the blessings of the internet, within a few minutes, people can see where the product is cheapest by using the sites which make a price comparison, learn the positive and negative aspects of the product by reading the user comments, and find another product alternative that satisfies the same need. These reasons have caused researchers to accelerate their studies on consumer preferences and product development areas.

So how do people choose products? What are the factors affecting people's preferences? How can a product be preferred among tens, hundreds or even thousands of its alternatives? Answering these questions is critical for the products to hold up in the market and for companies to survive in a competitive environment. Nagamachi says that even if manufacturers create thousands of different products, people only choose the product that appeals to their own needs and feelings (Nagamachi, 1997). Accordingly, product design after evaluating both the product features that people care about and people's perceptions and feelings about that product is of great importance for manufacturers to gain advantage at the market.

The main methods used in studies on consumer preferences and product development are Quality Function Deployment (QFD), Kano model, Conjoint analysis, Discrete Choice Experiment and Kansei engineering. One of these methods, QFD is a new product development method that dates back to 1966 and was developed by Shigeru Mizuno and Yuji Akao. The aim of QFD is to incorporate customer satisfaction into the product before it is produced, by developing a product using the voice of the customer (Mazur, 2021). It is used for maximizing customer satisfaction by including the spoken and unspoken needs into the design process (Mazur, 2015: 24).

Another method, Kano model, is developed as the theory of customer satisfaction and product development by Noriaki Kano in the 1980s. The Kano model is used to identify both implicit and explicit customer needs and to prioritize self-identified quality characteristics of products and services (Coleman, 2015: 1-2). The Kano model divides customer preferences into five categories: must-be quality, one-dimensional quality, attractive quality, indifferent quality, and reverse quality.

In addition, based on Luce and Tukey’s seminal paper on conjoint measurement (Luce & Tukey, 1964: 1-27), Conjoint analysis is a method used to elicit the product attributes that maximizes people’s satisfaction and to develop products according to these attributes. To do this, it divides the product into certain attributes and aims to determine them that satisfy the customers by ranking or rating the product alternatives created.

The Discrete Choice Experiment (DCE), also known as Choice-Based Conjoint (CBC) Analysis (Sawtooth Software, Inc., 2021), is based on Lancaster's new consumer theory approach (Lancaster, 1966: 132-157). Unlike conjoint analysis, in DCE studies that use experimental design and analysis, it is requested from people to choose the most preferred alternative among all product alternatives presented with a hypothetical scenario. In DCEs, where individuals have the right to choose no alternative presented, the product alternative that maximizes the utility of people is elicited.

Finally, Kansei engineering is a product development method presented by Mitsuo Nagamachi in 1970. Kansei is a Japanese word and is formed by combining the words Kan and Sei. Since there is no exact equivalent in other languages, it is used in the original language in the literature. It has many meanings such as image in the human mind, reaction to external situations, intuition, and interaction between mental activities etc. In Kansei engineering, Kansei is the word used to describe the product and express the product's image in mind. Kansei engineering is a technology where the image in people's minds about the product is transformed into design features. It aims to include people’s perceptions, feelings, and attitudes into the product design process. Thus, by using Kansei engineering, products that capture customers’ emotions will be designed (Nagamachi, 1995: 3-4).

According to Koç, these methods can be used alone proper to the purpose of the design problem or by using them in an integrated structure, they can provide an effective solution to the problem of reflecting customer demands and requirements to the product design (Koç, 2009: 11). Moreover, in the literature, there are studies in which the methods above are used together. A few of these studies are mentioned below.

The first of these studies is Tontini’s study, which integrates the Kano model and Quality Function Deployment. In his study, Tontini firstly shows the limitations of the two previously proposed methods for the integration of these two methodologies. According to Tontini, two methods focusing on the basic and excitement requirements are insufficient in providing basic requirements and arousing excitement. Therefore, he introduced the model proposed. He then tested his method on the development of a new mug of draft beer (Tontini, 2007: 599: 612).

In addition, Hartono and Chuan's study introduces a model that integrates the Kano Model and the Kansei Engineering. To demonstrate the relationship between service features and consumers' emotional behavior, a study was conducted with 100 tourists staying in 4- and 5-star luxury hotels and revealed which features have the most impact on customers' emotional needs (Hartono & Chuan, 2011: 987).

Moreover, Wang and Wu (2014: 177) offer a hybrid model that integrates the Kano model and Conjoint analysis, aiming to include customers' preferences and perceptions in their decision-making processes. They then use this model on the prioritization of smartphone variants by customer segments.

In the study in which Conjoint Analysis and Kansei engineering are used together, Schütte stated that in Conjoint Analysis, people prefer product alternatives according to whether they satisfy their needs, and while doing this their Kansei is also measured indirectly (Schütte, 2002: 44).

The starting point of the thesis is to directly measure Kansei measured indirectly by conjoint analysis and to reveal its relationship between product attributes. Therefore, in this study, a customer-oriented choice model reinforced by the integration of Kansei Engineering and Discrete Choice Experiment is proposed. The aim of this model is to determine both product attributes and perceptions and feelings about the product. Unlike studies where integration of Kansei Engineering with Conjoint Analysis is used, it is planned to obtain results that are closer to the actual choice behaviors, since people directly choose from the alternatives offered to them instead of ranking or rating the product alternatives.

This model, which can be used in the design of all existent or non-existent products and services, consists of two consecutive experimental studies. With the first experiment, the part worth utilities of product attributes will be found and therefore the product alternative that maximizes the utility of people is revealed. Then, with the second experiment, the relationship between these attributes and the perception and feelings evoked by the product will be elicited.

There are four chapters in this study. The first chapter includes Discrete Choice Experiment (DCE) methodology. The historical background and key terms of DCE will be discussed, the stages of a DCE are explained, and examples of studies in the literature are given in this chapter.

In the second chapter, Kansei Engineering (KE) methodology will be explained by giving the definitions of Kansei and Kansei engineering and the historical development of the method. After introducing Kansei engineering types and their representative examples from the literature, the steps in the Kansei Engineering process will be detailed.

In the third chapter, the proposed model will be introduced. First, it is mentioned the realities under why Discrete Choice Experiment and Kansei Engineering methodologies are integrated. Then the theoretical framework of the model will be drawn. Finally, the steps in the model will be explained in detail.

In the fourth chapter, the proposed model will be demonstrated on an example course design. All steps of the model will be shown in detail and explained how each component in the model will be handled throughout the product design process.

Finally, the study concludes by discussing the proposed model and its implications in the literature and practice.

CHAPTER ONE
DISCRETE CHOICE EXPERIMENT

People will be in consumption to fulfill their needs, and consumer behavior is an area that researchers have been working on for many years. The main reason for this is to increase the competitive advantage of companies that can perform main activities such as demand forecasting, price determination, product development by using the explanations of these behaviors. To explain consumer behaviors at aggregate level, individual level behaviors are analyzed.

Ben-Akiva and Lerman states a theory of individual behavior which has three characteristics as descriptive, abstract, and operational. What is meant by descriptive is that it tries to explain how people behave rather than emphasizing how they should behave. Being abstract means that it does not change according to certain situations and being operational is that it can be measured and explained with parameters/variables. However, there is no universally accepted theory that covers all these characteristics. Theories often differ according to the way behavior is observed. (Ben-Akiva & Lerman, 1997: 31).

Discrete Choice theories are modeled on the assumption that when an individual makes a choice, he will choose the alternative that provides the highest utility among the available alternatives, and it is impossible to design a model that always succeeds in predicting the chosen alternatives for all individuals. The reason for this is that the real utility of people consists of both observable and unobservable utility components. Therefore, using Thurston's (1927) random utility term, the probability of choosing an alternative among the available alternatives is defined by the probability of having the highest utility.

In addition, Lancaster proposed a new approach to consumption theory in 1966. According to him, people get utility from the attributes of the product, not from the product per se. An attribute can belong to more than one product and products can have more than one attribute. Therefore, the utility of the product is evaluated in terms of combinations of properties. For example, freshness is a property for both bananas and apples. However, when choosing apples, one evaluates the juiciness rather than the tenderness attribute (Lancaster, 1966(a): 14-15).

It is possible to model people's choice behavior using the two approaches above. DCEs using experimental design and analysis can be used for this. DCEs introduce hypothetical alternatives that they have created using the important attributes of products and services to people in the experimental environment by using various presentation techniques. After the introduction, people are asked to choose one of the available alternatives. As mentioned before, since they make this choice by considering the maximization of their utilities, important attributes of products and services can be revealed by using Discrete Choice Models after the experiment.

Before diving deep into DCEs, it will be effective to understand basic concepts such as utility, measurement of utility, and utility assumptions by introducing Economic Consumer Theory. The Economic Consumer Theory, which transforms a consumer behavior under certain conditions and various assumptions into a demand function, is the basic approach in modeling individual behaviors. It provides a good basis for understanding discrete choice studies. For this reason, before mentioning DCE, the key concepts and assumptions of this theory will be briefly mentioned.

Furthermore, DCE will be introduced, and its historical background will be given. Because DCE is also defined as choice-based conjoint (CBC) in the literature and therefore evaluated as a conjoint analysis method, similar and different aspect between DCE and conjoint analysis will be evaluated. After the DCEs of different product and services from different fields are mentioned, the key terms necessary to understand DCE will be summarized. Finally, DCE stages will be mentioned.

1.1 ECONOMIC CONSUMER THEORY

Consumption is an activity that takes advantage of the usefulness of goods and services to fulfill people’s needs. It is also the final aim of an economic activity and a welfare measurement, because fulfilling the needs will only be possible with consumption (Bulmuş, 2008: 20).

People have finite income and infinite needs, and to fulfill their needs they consume goods and services. These goods and services vary in their characteristics. For example, strawberry, hamburger, bus transportation, telecommunication services have different characteristics. But they all have one common thing. Every good and service consumed to fulfill a need - no matter what the need is- eventually awaken a sense of satisfaction in the consumer. In economics, this sense of satisfaction is called utility (Bulmuş, 2008: 20). In other words, utility is the degree to which the goods and services meet the consumer's needs. Utility is the basis of consumer demand, and the consumer always chooses goods and services that gives more utility (Ünal & Tunalı, 2011: 4)

The possibility of measuring the utility obtained from the consumption of goods and services has divided the economists in two sides. One side argued that the utility can be measured, while the others argued that the utility cannot be measured but can be ranked. These two sides are Cardinalists and Ordinalists respectively (Kamilçelebi, 2013: 448).

For the first time Economists, as Gossen, Walras and Marshall, have studied utility and utility function, they hoped that individual utilities can be measured in simple units. Because if it was possible to measure, comparing and ranking the interpersonal utilities would be also possible. Cardinal measurement of the utility is the expression of utility with a certain number and the Economists who advocate this measurement are called Cardinal Utilitarians (Cardinalists). According to the Cardinalists, the utility can be measured with an abstract amount called "util" (Sönmezler et al., 2019: 35).

The cardinal utility assumptions are as follows (Bulmuş, 2008: 21-22):

1) Rationality: The consumer is rational. Her purpose is to maximize the utility from the consumption of goods and services. When performing utility maximization, she is conscious and always considers her limited income.
2) Cardinal Utility: Utility is a concept that can be measured and expressed in a certain number. The unit used in the measurement not as important as the constancy of measured value. Cardinal Utility Theory used money as a unit of measurement.
3) Diminishing Marginal Utility: During the consumption of a good, the utility of the first unit is always greater than the other units of the good. If consumer does not give a break to consumption, the utility obtained from unit consumed continues to diminish.
4) Addible Utility: The utility of each good is independent to the other, but the utility from the consumption of the goods or services bundle depends on the amount of consumption of each of the goods and services constitutes this bundle.

$$U = f(q_1, q_2, \dots, q_n);\ q_i \geq 0\ ; i = 1,2, \dots, n$$
$$U = U_1(q_1) + U_2(q_2) + \cdots + U_n(q_n)$$

Today, almost all Economists have agreed that the utility function cannot be cardinal. It is not possible to measure the utility of any good in terms of utility units. In fact, according to these Economists, it is not necessary to measure the utility. The main task of the utility function is to distinguish the more favorable good from the less favorable one. When deciding which goods to buy and how much, the consumer prioritize the goods according to their own benefit. The utility function then serves as an indicator for the usefulness of the various combinations of goods against each other. As a result, according to today's Economists, the utility function is ordinal, not cardinal (Bulmuş, 2008: 25).

Ordinal utilitarians argue that the utility cannot be measured but that the order of preference can be determined by comparing the goods with each other in terms of utility.

The utility function that provides the ordering of the bundles of market goods is called the Ordinal Utility Function. The Ordinal Utility Function ranks the bundles of goods from the most preferred to the least preferred. However, this ranking does not indicate "how much" more the good is preferred. Values vary from person to person, and interpersonal utility comparison is not possible.

According to Ordinal utilitarians, faced with the consumption of two goods A and B, the consumer will either prefer one of these goods to the other or remain indifferent between the two (Yıldırım et al., 2015: 37).

- Consumer prefers good A to good B ($U_A > U_B$)
- Consumer prefers good B to good A ($U_B > U_A$)
- Consumer is indifferent between good A and good B ($U_A = U_B$)

Ordinal Utility Theory Assumptions are as follows (Ünal & Tunalı, 2011; Ünsal, 2010: 153-155):

1) Completeness: The consumer is able to compare and rank all possible bundles of goods. That is, the consumer either prefers A to B, or prefers B to A, or remains indifferent between them because A and B provide equal satisfaction to the person. These preferences ignore costs which means that the consumer may prefer pizza to pasta but can buy pasta because it is cheaper.
2) Transitivity: A consumer facing three different baskets, such as A, B and C, preferring A to B and B to C. In other words, there is an internal consistency in an individual's preferences. (If A> B, and B> C, then A> C)
3) Nonsatiation (More is better than less): Most consumers prefer more to less, or in other words, “More is always better, even if just a little better.” If A shows a bundle of goods with two goods and B shows a bundle of same but more goods, the consumer's utilities on these bundles will be $U_B > U_A$.

This assumption, which can be summarized as being less than good or more than less, means that there is no saturation point in any good. Good for goods. Less of an unwanted product such as noise is always preferred.

4) Continuity: The existence of an infinite commodity composition that provides the same satisfaction prefers continuity in preferences. There is another basket at least as good as the goods basket A, in the path of the goods baskets from the goods basket B, which is not preferred to the goods basket A, to the goods basket C, which is preferred to the goods basket A. In other words, there is a goods basket D in which the consumer is indifferent compared to the goods basket A from the goods basket B, which is not preferred to the goods basket A, to the goods basket A from the goods basket A to the preferred basket C.
5) Strictly Convexity: When we connect two points on the indifference curve, each point on this line will remain in the preferable region. Therefore, any point on the line joining these two points indicates a higher level of utility. According to this hypothesis, if the consumer is indifferent between A and B goods baskets, he prefers a basket C which consists of the weighted average of A and B goods baskets to both goods baskets.

$$C = \lambda A + (1 - \lambda)B, (0 < \lambda < 1);\ A/B \Rightarrow CPA\ and\ CPB$$

According to Bulmuş, the assumption of continuity is not realistic enough. Because all goods and services consumed in real life cannot always be divided in a meaningful way. Assuming that the goods consumed is homogeneous, that is divisible in spite of this drawback, provides the possibility of using mathematics as a means of expression and analysis. Therefore, today's economists accept that the utility function is continuous (Bulmuş, 2008: 25). Discrete Choice Experiment, which arises from the assumption that goods and services are discrete, will be explained later in the chapter.

1.2 DISCRETE CHOICE EXPERIMENT

DCE is an attribute-based method used for utility measurement. DCEs present the product alternatives within a choice sets to the participants with hypothetical scenarios using all possible choice alternatives. Each choice sets presented contain two or more alternatives and the participants are asked to choose one alternative from these sets (Ryan et al., 2008: 13). DCEs are frequently used in many fields such as marketing, transportation, health economics to analyze consumer behavior that requires discrete and qualitative choices (Louviere et al., 2008: 360).

Discrete Choice Experiment (DCE) represents the approach used to estimate the relative importance of product attributes influencing individual's product choices. It requires individuals to choose their preferred discrete product alternative from a set of hypothetical alternatives. Each product alternative is created with different combinations of specified attributes (Louviere et al., 2008: 360). Therefore, when choosing a product, the individual compromises some of the attributes, and this compromise reveals the relative importance of attributes.

DCE is a methodology based on the assumption that all products and services can be identified by the characteristics and aims to reveal individuals' preferences over the products and services (Lancaster, 1966(a): 14). Basically, to reveal the preferences, separating the characteristics of a product and presenting various alternatives created from these characteristics through a survey under a hypothetical scenario constitutes the essence of DCE. In DCE, it is assumed that people choose the most preferred among the choice sets which include product alternatives. This is in fact consistent with assumption of Economic Consumer Theory that people are rational and pursue utility maximization.

Methodology is called the Discrete Choice Experiment because of these reasons:

- It is a 'choice' because people choose the alternative that gives the maximum utility among all alternatives within a choice set.
- It is an 'experiment' because the choice process actualizes within hypothetical scenario through hypothetical alternatives.
- It is also 'discrete' because choosing one alternative exactly means not choosing any other alternatives in the choice set. (Louviere et al., 2010).

Moreover, DCE is an optimization problem defined in neoclassical consumer theory, in which the consumer with traditional characteristics prefers the product that will maximize her utility (Ryan et al., 2008: 14).

DCEs, also named as stated choice method, choice experiment, choice-based conjoint analysis, or discrete choice conjoint analysis, are used to determine the characteristics of products and services that maximize people's utility. With DCE, it is possible to work for those products and services that have been put on the market before, as well as for those who are at the idea stage. In this way, the important characteristics of the products that have not yet been produced can be determined by the people and these products can enter the market in an advantageous way.

1.3 HISTORICAL BACKGROUND OF DCEs

The traditional economic consumer theory was mentioned above. In traditional theory, it was thought that consumers evaluate the whole of products and services and make their choices based on their psychological tastes rather than products' characteristics (Debreu, 1960; Johnson, 1958). However, Discrete Choice Experiment has its roots in Lancaster's Consumer Theory and Thurstone's Law of Comparative Judgment.

Lancaster's Consumer Theory assumes that products do not have direct influence on preference and utility. Preference and utility are related to the product characteristics (Lancaster, 1966: 14). Lancaster assumes that in a consumption activity where a product or combination of products is the input, and the sum of the product characteristics is the output. It is assumed that individuals have a preference over all possible set of characteristics, and the ranking is according to the least preferable characteristic combination from the most desirable one. Therefore, the aim is to estimate the utility function of consumers subject to the constraints of the situation (Lancaster, 1966: 132).

In addition to Lancaster's theory, DCE can also be explained by Random Utility Theory (RUT). Random Utility Theory is based on Thurstone's Law of Comparative Judgment. Law of Comparative Judgment defined as a model used for any pairwise comparison measurement. Measurements represent how we perceive things, rather than being measurements of actual physical properties. This type of measurement is the focus of psychometrics and psychophysics (Thurstone, 1927: 273).

Thurstone's law formed the basis of the Random Utility Theory (RUT). According to RUT, individuals prefer the alternative that provides them highest utility from a set of product alternatives. It assumes that although individuals make choices that maximize their utility, their utility is random, and their actual behavior cannot be modeled. There is also a random component in utility maximization (Thurstone, 1927: 284-286).

RUT suggests that people do not make their decisions randomly, only their utilities contain random components. Consumer behaviors are investigated with Random Utility Models supported by RUT (Ryan et al., 2008: 14-16), and RUMs which are used in DCE analysis and emerge from Econometrics, are based on the work of Nobel Prize winner McFadden in the 1970s. DCE studies have accelerated with the development of computer programs that speed up the design of DCE studies and ensure that they reach more participants.

To roughly summarize Random Utility Models (RUMs), in other words, Discrete Choice Models, let the individual n choose an alternative from J number of alternatives. $j = 1,2,\ldots,J$. There is a utility that an individual will derive from all alternatives. For example, the utility obtained from the j[th] alternative is U_{nj}. While making a choice, the individual chooses the alternative that maximizes his utility. So, if individual n chooses i[th] alternative, $U_{ni} > U_{nj} \ \forall\, j \neq i$ (Train, 2009: 14-16).

Although these utilities are known by individual, researchers cannot predict the utilities. Thus, the function representing the utility of the individual n, includes the attributes of the products $(x_{nj}\ \forall j)$ and the attributes of the individual n (s_n). The representative function is shown as follows (Train, 2009: 14-16)

$$V_{nj} = V(x_{nj}, s_n)\forall j \qquad (1.1)$$

An individual's choice behavior cannot be predicted directly $\left(U_{nj} \neq V_{nj}\right)$ and the utility function includes unobservable factors (error term). Therefore, the function of the utility obtained by the individual n from the alternative j is as below (Train, 2009: 14-16).

$$U_{nj} = V_{nj} + \varepsilon_{nj} \qquad (1.2)$$

Here ε_{nj} is the difference between the real utility U_{nj} and the utility that the researcher can observe V_{nj}. The researcher does not know ε_{nj} and treats this term as random. Accordingly, the probability of n individuals choosing alternative i is as follows (Train, 2009: 14-16).

$$P_{ni} = Prob(U_{ni} > U_{nj}\,\forall j \neq i) \qquad (1.3)$$

$$= Prob(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}\,\forall j \neq i)$$

$$= Prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \, \forall j \neq i)$$

The cumulative distribution for which the error term $(\varepsilon_{nj} - \varepsilon_{ni})$is less than the observed utility $(V_{ni} - V_{nj})$ can be written using the density $f(\varepsilon_n)$ as follows (Train, 2009: 14-16).

$$P_{ni} = Prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \, \forall j \neq i) \qquad (1.4)$$

$$= \int \varepsilon \, I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \, \forall j \neq i) f(\varepsilon_n) d\varepsilon$$

In this expression, which shows the multidimensional integral of the density of the unobservable part of the utility $(f(\varepsilon_n))$, $I(.)$ is an indicator function and the takes a value of 1 if the expression in the parentheses is true and 0 if else (Train, 2009: 14-16).

1.4 LITERATURE REVIEW

Discrete Choice Experiment is an effective methodology that can be used to reveal the preferences of decision makers for every product and service from every sector. For this reason, examples of DCE from different sectors will be shown in the literature review.

Food: Verma and Thompson (1999: 891-908) were conducted a DCE study to determine the preferences of university students over pizza restaurants. In the study, 15 different 2-level attributes were used for cost, delivery, flexibility, product, and service quality constructs. In the study in which 32 choice sets were evaluated by 89 participants, it was aimed to reveal the restaurant preferences and selection patterns of the students. With the study in which data analysis was done with multinomial logit (MNL), it was concluded that DCE can be used as a support tool in the operational decisions of companies.

Tourism: Unbehaun et al. (2008: 36-47) have applied DCE to reveal the possible changes in the skiing preferences of the winter sports tourists due to climate change. Eight attributes with 2 to 4 levels that concern the performance of the ski destination, environmental aspects, costs, and travel time were selected for the experiment and four choice sets with two hypothetical ski destinations were shown to respondents. Results were analyzed with LIMPED 8.0 in the study, in which 538 people participated. It has been concluded that offering additional services that will affect people's preferences can help not to seriously decrease tourist mobility in the region.

Finance: Schlereth (2014: 595-616) carried out a DCE study in collaboration with the German online retail bank. The purpose of the study is to reveal the client preferences to decide on the pricing for the fee-only financial advisory service. Study is conducted by using flat pricing plan and volume pricing plan. At the end of the study, it was revealed that both plans were equally preferred. But it has been found that only if the service provider uses a volume pricing plan, it can increase its revenue by 12 per cent.

Psychology: Solino and Farizo (2014: 1-7) have conducted a DCE study to show the influence of personality traits on environmental valuation. The experiment is applied to 2224 households in the region where resin tapping is carried out in central Spain. Six features with 3 to 4 levels were used in the study and data analysis was performed by mixing the Random Parameter Logit model and the Latent Class model. As a result of the study, it was revealed that personality traits of individuals play a role in environmental product and service preferences.

Art: Hall et al. (2016: 141-165) has carried out a DCE study of the bundling strategy that can be realized as package deals because of solving the problem of declining attendance and increasing the demand for loyalty on art and opera in Australia. DCE was conducted together with four focus group studies for data collection and data analysis. 1340 participants have made choices for 3 package deals that have 5 attributes with 3 to 5 levels. Results were analyzed with SPSS and a customized CBC package program, and data analysis was completed using a multinomial logit model.

Education: Sheppard and Smith (2016: 140-149) conducted a DCE study to uncover students' demands. In their study, they used the data from a postgraduate institution in the UK, and it was revealed that staff expertise, and flexibility of the teaching platform are two features that are effective in students' post grade program preferences.

Accounting: Turner and Coote (2017: 158-182) conducted a DCE study to illustrate how the DCE is used in the accounting research. In this study, DCE is applied in the capital budgeting case The study is important because it is the first DCE application in the field of accounting.

Healthcare: Bahrampour et al. (2018: 676-683) conducted a DCE study to determine the preferences of patients over the service quality of hospitals. In the study, 6 attributes with 2 or 3 levels were used and 12 different alternatives were evaluated over 2 hypothetical hospitals. In a study involving 167 patients, it was revealed that the most important feature that patients consider in service quality is physical examination. This attribute is followed by cleaning and training after discharging.

1.5 DISCRETE CHOICE EXPERIMENTS VS. CONJOINT ANALYSIS

The Discrete Choice Experiment is also called Choice-based Conjoint (CBC) in the literature (Sawtooth Software, Inc., 2021). Thus, DCE is assumed to be a type of Conjoint analysis. However, they differ in terms of both their theoretical background and applications.

Louviere et al. (2010(a): 58) states that most studies that do conjoint analysis actually do DCE. For this reason, Louviere also claims that most researchers have difficulty in distinguishing these two methods from each other and even do not know how they are differed. In this section, Conjoint analysis and DCE will be mentioned, and their similar and different points will be emphasized.

Conjoint analysis (CA) is a method that requires individuals to rate or rank alternatives created using various features and levels (Ryan et al.,2008). In a CA study that requires ranking, the participants indicate their preferences for each alternative by ordering them considering their importance, while in a CA study that requires rating, they score each alternative, thus showing their willingness to prefer (Boyle et al., 2001: 441-442).

However, when choosing a product, people rarely rank or rate product alternatives. They usually choose directly from alternatives. For this reason, Conjoint Analysis (CA) are insufficient to reveal the actual decision-making behavior of people. In addition, CA is not compatible with neoclassical economic theory, which is based on discrete choice rather than ranking or ranking. Therefore, the models used to explain uncertainty in typical economic theory are not applicable and it is not supported by economic theory, Furthermore, comparison of the stated preference data with the revealed preference data is inappropriate, as the resulting data do not represent actual decision-making behavior (Louviere et al., 2010(a): 63-65).

DCEs, like CAs, contain product alternatives created from certain attributes and levels. Again, they are used to reveal people's preferences on these product alternatives. In DCEs, however, individuals show their choice by choosing one from two or more alternatives. This makes the experiment be more realistic as it resembles choices in daily life (Louviere et al. 2010(a): 62-63; Ryan et al., 2008: 37).

1.6 KEY TERMS FOR DISCRETE CHOICE EXPERIMENT

The basic concepts for understanding the Discrete Choice Experiment will be briefly mentioned.

Decision makers: The ones who are tried to be learned about their choices over alternatives. They can be any decision-making unit as people, households, firms, or organizations etc. (Ben-Akiva & Lerman, 1997: 33)

Attributes: The characteristics or features of products and services. Attributes contain manipulated variables for each observation. These variables are also expressed in the literature using the terms factor, explanatory, or independent variables (Ben-Akiva & Lerman, 1997: 34).

Attribute Levels: They are used for describing each attribute. It can be numerical or verbal and express the values observed for each attribute and is also referred to as factor level in the literature (Louviere et al., 2010(b): 83-84). For example, if the camera resolution of a smartphone is an attribute, 8 megapixels, 10 megapixels and 12 megapixels represent 3 levels of this attribute.

Alternative: Any hypothetical product created by the combination of various levels of product attributes. Alternatives are also called profile, stimuli, and treatment in the literature. After determining the attributes and attribute levels, the researcher creates alternatives by combining one level of each attribute (Hair et al., 2007: 406).

Factorial Designs (FDs): A design in which all levels of an attribute are combined with all levels of all other attributes (Louviere et al., 2010(b): 84). For example, imagine three attributes for a smartphone, all of which contain two levels. When these are camera resolution (8-megapixel, 10-megapixel), color (black, white) and price (5000 ₺, 7000 ₺), all possible smartphone combinations (2x2x2 = 8 smartphones) are as in the table below.

Table 1: Example Factorial Design

Smartphone Combination	Camera Resolution	Color	Price
1	8-megapixel	Black	5000₺
2	8-megapixel	Black	7000₺
3	8-megapixel	White	5000₺
4	8-megapixel	White	7000₺
5	10-megapixel	Black	5000₺
6	10-megapixel	Black	7000₺
7	10-megapixel	White	5000₺
8	10-megapixel	White	7000₺

In general, a factorial design is a factorial enumeration of all possible combinations of attribute levels. Such a complete enumeration is often referred to as full factorial. Factor designs have very attractive statistical properties in terms of estimating the parameters of general linear models and/or testing hypotheses based on such models. In particular, full factorial designs ensure that all relevant attribute effects are truly independent. In fact, it can be said that the attributes are independent by design. Therefore, in such models, the relevant statistical effects or parameters can be estimated independently of each other. In addition, all possible effects associated with analysis of variance or multiple linear regression models can be estimated from a full factorial (Louviere et al., 2010(b): 85-86).

Fractional Factorial Designs (FFDs): As an alternative to full factorial design, the design of profiles using subsets of attributes is called fractional factorial design. It is aimed to reduce the number of alternatives created in this design and not lose orthogonality of design during this reduction (Hair et al., 2007: 408).

Choice Set: In other words, design, is set of alternatives created using experimental design principles. Choice sets need to be optimally designed. For this, they can be orthogonal or balanced. If individuals are shown all levels of all attributes in equal numbers throughout the survey, this design is called balanced design. In orthogonal design, the change in each attribute level is independent of other attributes' levels. A change in a level of an attribute is separated from an experimental error and a change in other attributes (Hair et al., 2007: 407).

Choice sets must have three characteristics to be suitable for discrete choice framework. They should be mutually exclusive, exhaustive, and finite. By mutually exclusive, it is implied that choosing an alternative means all other alternatives are definitely not chosen. Being exhaustive implies that the choice set must contain all alternatives created from product attributes. Finally, being finite means that the alternatives can be counted, and this counting process ends sooner or later (Train, 2009: 11).

Fixed Alternatives: Also called holdout profiles, the tasks that are not used to estimate the part worth but used for the validity and reliability of the experiment (Sawtooth Software, 2021).

Composition Rule: The rule that defines how people combine attributes while determining product's overall utility. It can be an additive model, which includes the collection of main effects, or a more complex model, which includes combining the attributes with each other and examining the interaction effect (Hair et al., 2007: 407).

Main Effects: Defined as how much each attribute level affects the total utility of the product. Measuring the direct effect of price, camera resolution, and color on smartphone utility in the smartphone example (Hair et al., 2007: 409).

Interaction Effects: Defined as the joint evaluation of the effects of interrelated attribute levels. An example is the evaluation of the effects of price and camera resolution together in the smartphone example (Hair et al., 2007: 408).

Additive Model: Also known as the main effects model, the rule is calculation of the total utility value of the product by adding up the part-worth utilities obtained from the levels of the attributes (Hair et al., 2007: 407).

Part-Worth: The utility value that an individual assigns to each attribute level when evaluating a product. By summing these values, the total utility value obtained from the product is calculated (Train, 2009).

Pairwise Comparison: A method of presenting two alternatives to individuals and asking them to choose the alternative they prefer (Hair et al., 2007: 409).

Full-Profile: A method that involves presenting the alternatives created by using all levels (factors) to the individuals and collecting the evaluations. In this method, basic principle is that the alternatives contain one level of each attribute (Sawtooth Software, 2021).

Trade-off Analysis: In this method, the aim is to measure the effect of the levels of one attribute. For this, people are presented with alternatives where only the levels of one attribute change and the other attribute levels remain the same (Yalçın, 2016: 18).

Survey: It is a way of evaluating the properties of a hypothetical product. Louviere et. al (2010) defines all data collection tools used to reveal the choices or preferences of the participants with "survey". These surveys differ according to the products subject to study. While only "paper and pencil" would be sufficient for the work of relatively simple products that everyone knows and will not have difficulty in choosing; In complex products where people do not have a good command of their characteristics, the survey study becomes more complex and makes use of new technology tools. Advanced computer-aided surveys using multimedia tools such as audio, video and video are used in the work of such complex products (Louviere et al., 2010(b): 20).

1.7 DISCRETE CHOICE EXPERIMENT PROCESS

The discrete choice experiment consists of five stages. In the first stage, the problem definition is made. Here, what is meant by the problem is which product is the subject of the choice experiment. In the second stage, the attributes of the product are determined, and levels are assigned to the attributes. In the third stage, an experiment is designed using attributes and levels. In the fourth stage, the experiment is conducted, and answers of the participants are collected. In the final stage the data is analyzed using discrete choice models.

1.7.1 Problem Definition

The first stage of DCE is problem definition. By problem definition, it is meant to determine for which product or service the experiment will take place. Since all products and services have certain attributes/characteristics, DCEs can be applied to all products and services.

After specifying the product, which target group the product will appeal to and with whom the experiment will be conducted are also specified at this stage. The target group will directly affect the results of the study as each group will have different desires for the product. Therefore, the researcher should be careful in choosing the product and target group.

1.7.2 Determination of Attributes and Attribute Levels

In the second stage, the attributes of the product are determined. In DCEs, people evaluate product alternatives. These alternatives are formed by combining the attributes of the product with various methods. After all, the part worth utilities of product attributes are revealed by collecting and analyzing people's preferences on alternatives.

An attribute or an attribute level cannot be removed from the analysis after the experiment has taken place. For this reason, it is very critical to determine the properties and levels correctly before design (Hair et al., 2007: 423).

Ambiguous expressions should not be used when naming attributes and levels. People should easily understand what they are choosing when making a choice. At the same time, all attributes and their levels must be understood in the same way by the participants (Orme, 2002: 1).

1.7.3 Experimental Design

After the attributes and levels are determined, the experiment is designed. Experimental design consists of two main stages. First, the presentation method used in the experiment is chosen. Then the design method of the alternatives is determined.

1.7.3.1 Presentation of the Alternatives

The amount of information to be shown to people varies according to the chosen presentation method. Two presentation methods are generally used in DCE studies. These are full profile, pairwise comparison and trade-off methods (Hair et al., 2007: 431). In order to understand the presentation methods, the attributes used in

Table **1** will be visualized in accordance with the methods.

In the full profile method, three or more product alternatives generated using various levels of all attributes are shown to the participants and the choices of the participants are collected (Hair et al., 2007: 431). Figure 1 shows an example of full profile presentation of smartphone alternatives.

Figure 1: Full Profile Presentation

Alternative I		Alternative II		Alternative III	
Camera Resolution:	8 megapixels	**Camera Resolution:**	10 megapixels	**Camera Resolution:**	10 megapixels
Color:	Black	**Color:**	Black	**Color:**	Black
Price:	7000	**Price:**	5000	**Price:**	7000

The pairwise combination is can also be chosen for presentation. In this method, the participants evaluate the product alternatives in pairs and make their choices. Its effects are more limited compared to the full profile presentation. Because in this presentation method, not all attributes are evaluated at the same time, and only two alternatives are evaluated. Generally, the goal is to determine which of the alternatives has the greater effect (Hair et al., 2007: 432). An example is shown in the Figure 2 below.

Figure 2: Pairwise Comparison

Alternative I		Alternative II	
Camera Resolution:	8 megapixels	**Camera Resolution:**	10 megapixels
Price:	7000	**Price:**	7000

The third presentation method is the trade-off method, which involves participants evaluating all levels of the two attributes of the product on a matrix. This method is preferred in traditional conjoint studies rather than DCE studies. Because instead of specifying the choices on a matrix, ranking or rating on the matrix will be more effective. Below is an example of a presentation over a trade-off matrix.

Figure 3: Trade-off Matrix

		Color	
		Black	White
Price	5000		
	7000		

1.7.3.2 Profile Design

The design method to be used during the generation of alternatives is decided. Generally, these are full factorial design and fractional factorial design. In full factorial design, alternatives are generated using all possible combinations of all levels. This design should be preferred in studies with less attributes and levels. The reason for this is that as the number of attributes and levels increases, the evaluation of alternatives will become more difficult. For example, if 2x2=4 designs are required for two-leveled two attributes, 3x3x3=27 designs are required for three-leveled three attributes (Hair et al., 2007: 432).

Full factorial designs often contain too many alternatives to be evaluated, as studies are often multi-attributed and multi-level. For this reason, the number of alternatives is reduced by considering that they have balanced and orthogonal design. Fractional factorial designs may be preferred instead of full factorial designs. In fractional factorials, it is aimed to design profiles with subsets of attributes without loss of information. Three types of design are possible: manual, computer optimization, or computer randomization. D-optimal design should be preferred in a computer aided design (Orme and Chrzan, 2000: 5).

1.7.4 Conducting the Experiment

While conducting the Discrete Choice Experiment, first the product is introduced to the respondents through a hypothetical scenario. This scenario explains which attributes they will evaluate for which situation. An example hypothetical scenario is ‘You are now in front of the detergent aisle in a supermarket. You will choose a detergent to wash your child's school uniforms. The attributes you will consider when choosing are form, content, and price of the detergent. Your evaluation criteria are whether the detergent is solid, liquid or capsule, whether it contains heavy chemicals or not and the price of 20, 30 and 50 TL. If you only had to choose from among the four alternatives shown to you and you could have chance to choose none of them, what would be your detergent choice?’

Then, alternatives are presented with the chosen method. Figure 4 shows an example of a choice set created for the hypothetical scenario above. In the experiment, respondents are asked to make a choice from the alternatives presented them.

Figure 4: Example of a Choice Set

	Alternative 1	Alternative 2	Alternative 3	Alternative 4	
Form:	Solid	Liquid	Liquid	Capsule	I would not choose any
Contains heavy chemical:	Yes	Yes	Yes	No	
Price:	20 TL	20 TL	30 TL	50 TL	

1.7.5 Analysis of the Experiment

Five models are generally used when analyzing the data collected by the experiment. These models are logit, generalized extreme value (GEV), probit, mixed logit, and Hierarchical Bayesian Estimation. The models will be briefly mentioned.

Logit method is the most used model among Discrete Choice Models. It is assumed that the unobserved factor for all alternatives is the Independent and Identically Distributed (IID) extreme value. Therefore, unobserved factors are not related to alternatives and have the same variance for all alternatives. These assumptions are the reasons that the method is used most widely as they provide convenience in estimating the choice probability. However, the assumption that each alternative is independent of each other is not realistic. The factors affecting the choice are somewhat independent. For this reason, alternative models have been developed that do not use the logit's independence assumption (Train, 2009: 18).

Another model, the GEV, involves generalizing the extreme value distribution. Unlike the logit model, it allows correlation on alternatives and collapses with the logit model when the correlation is zero. GEV is a model with closed-form choice probabilities and do not need simulation for estimation. Shortly, in GEV model, alternatives are placed in the same nest when there are unobservable factors with the same correlation for all alternatives, and in a different nest when there is no correlation (Train, 2009: 18).

The third method, probit model involves the assumption that the unobservable factors have a joint normal distribution. It can include any correlation and heteroskedasticity in the model with the full covariance matrix and apply to the choice sequences over time assuming unobservable factors are jointly normal over the alternatives. The most important advantage of the model is its flexibility in evaluating the correlation of alternatives and time, and its limitation is the assumption of normal distribution. Unobservable factors are not always normally distributed. Making this assumption contradicts the fact that the distribution is positive because its density is on both sides of zero (Train, 2009: 18-19).

The mixed logit allows for any distribution of unobservable factors and can be used to predict all choice models. Its defining feature is that it can separate the unobservable factors into two groups. The first part of this group includes the factors correlation and heteroskedasticity, while the second part includes the IID extreme value. The first part can have both normal and non-normal distributions (Train, 2009: 19). Although the model has been known for a very long time, it was not fully implemented until simulation techniques were developed. After that, it easily calculates choice probabilities using simulation techniques. It is not constrained by the assumption of normal distribution and avoids the three limitations of logit by including random taste variation, unrestricted substitution pattern, and correlation of unobservable factors in the model (Train, 2009: 134). Since this model will be used in the study, it will be explained in detail in the Chapter Three.

The final method defined as Hierarchical Bayes because it contains a hierarchy of parameters used to estimate mixed logit parameters. It borrows information from the population when estimating part worth utilities for individuals and provides satisfactory results even with less data. At the upper level of hierarchy, it is assumed that the part worth utilities of individuals are multivariate normal distributed, and at the lower level of hierarchy, it is assumed that the probability of individuals choosing certain alternatives is explained by the multinomial logit model. Since this method will also be used in the model, it will be explained in detail in the Chapter Three.

CHAPTER TWO
KANSEI ENGINEERING

Not everyone can draw the perfect circle, but when asked about the ‘perfect circle’, the image of it appears in everyone’s mind (Schütte et al., 2004: 219). Also, even though one cannot describe this circle in words, she can distinguish which one is perfect in several different circle drawings. With this and many other examples, it can be argued that the images in people's minds can be embodied. The name of this embodiment is called Kansei engineering (KE) in product development. Kansei engineering aims to reveal more than what is said about a product. It is a methodology that adds hidden, subjective product features into the design process.

This chapter gives the definitions of Kansei and Kansei engineering, the historical development of Kansei engineering methodology, and the types of KE. Then, Kansei engineering methods and their representative examples from the literature will be presented. Finally, the steps in the Kansei Engineering process will be explained in detail.

2.1 DEFINITION OF KANSEI

As claimed in Ethnologue, 7117 languages are spoken today. While 23 of these languages are spoken in half of the world population, 40% are spoken by less than 1000 people and are therefore in danger of extinction. (Eberhard et al., 2020) Considering that all these languages contain thousands of words, we can infer those billions of words are spoken in the world. Some of these words don’t have exact definition in other languages, and the word Kansei is one of them.

Kansei (感性) is a Japanese word which is a combination of two characters Kan and Sei. In the Nelson’s Character Dictionary, these characters are defined as follows:

Kan (感): feeling, sensation, sentiment, sense, emotion; impression, intuition, perception, sensibility; influence; touch.

Sei (性): sex, gender; nature, attribute

The two meanings of the word Kansei in Japanese's most popular dictionary edited by Izuru Shinmura are as follows: “receptivity of sensation or perception stimulated in the external world through sense organs.” and “feeling, impulse or desire stimulated by sensation.” (Shinmura, 1998; Toho, 2006).

In addition to the dictionary definitions, Harada made a holistic study about the word Kansei. He examined the studies related to Kansei and analyzed the definitions in these studies by cluster analysis. As a result of his study, he revealed 5 different dimensions of Kansei. According to Harada, “Kansei is (1) a subjective and unexplainable function, (2) a mental function creating images, (3) the interaction of intuition and intelligent activity, (4) the ability of reacting and evaluating external features intuitively and (5) besides its innate nature, it consists of the cognitive expression of acquired knowledge and experience.” (Harada, 1998: 22). Then, based on his analysis, he described Kansei as “an internal process (a high function) of the brain, involved in the construction of intuitive reaction to external stimuli.” (Harada, 2003: 49-51).

Again, in the 2000s, Nagamachi, the pioneer of Kansei engineering, described Kansei as “individual’s subjective impression from a certain artifact, environment, or situation using all the senses of sight, hearing, feeling, smell, taste as well as recognition.” (Nagamachi, 2006: 27).

The meaning of the word Kansei from the Kansei engineering perspective was again explained by Nagamachi as “consumer’s psychological feeling and image regarding new product.” (Nagamachi, 1995: 4). When the customer enters the store to buy a new product, the image of the product he wants to buy is ready in his head. She expresses this image with certain words. So, Kansei covers both the image in the customer’s head and the words used to express this image.

2.2 KANSEI ENGINEERING

According to Lawrence D. Miles, there are two broad types of product functions – use functions and esteem functions. While use functions are the functions that affect the product to perform, esteem functions are the functions that affect the product to sell (Miles, 1961: 11-14). To make it clear, if customer asks product that helps him to solve a problem or accomplish an opportunity, he seeks to understand the use functions of that product. If customer wants a product that makes him look good or feel good, he searches for esteem functions of a product.

Today, customers consider the use functions of the product – functional features, as well as the use functions which are the hidden product features that will make them happy, make them look beautiful or increase their status etc., while choosing products, and with the emergence of 'functional equivalency' in product development with advanced technology, customers started to have difficulty in distinguishing the products. This has resulted in customers basing their final decisions on more subjective reasons when choosing products. Therefore, we can say that subjective (hidden) features dominate the functional features in selection process.

Furthermore, product-out and market-in are two distinct concepts in product development. While product-out concept refers to developing a product based on a company's strategy without giving any importance of what customer wants, market-in concept focuses on developing a product based on customers' perceptions. For this reason, terms such as consumer-oriented, consumer-centered, user-friendly that support market-in concept have settled in all product development processes from the idea stage to the end user stage. For this reason, consumers' perceptions and feelings are accepted as 'invaluable' by manufacturers. (Nagamachi, 2006: 27)

So, what does valuable or good mean? The terms good or valuable express that products are made based on consumer preferences. These preferences are psychological constructs with three dimensions as perceptual, emotional, and behavioral. They are mainly the degree to which consumers like the product (Chuang et al., 2001: 247-248). Therefore, products which pay attention to the consumer preferences are deep enough to know exactly what the consumer wants and can be easily placed on the market (Nagamachi & Lokman, 2016: 1-2).

In addition, the balance of Kansei and creativity is very important for products to be sensed as good/valuable. According to Nagamachi and Lokman (2016: 7), 60-70% of a product should match the customer Kansei, and the remaining 30-40% should be left to the creativity of the designer in order to make the customer experience the "wow" moment. If a customer meets a product that matches more than 70% of her Kansei, it can be found "cliché" as it will likely look very similar to a product she has seen before, whereas when faced with a product that matches with less than 60% of her Kansei, it may be perceived as "future-oriented" enough to make her think she doesn't need it.

Hence, the birth of Kansei engineering (KE) is relying on producing goods that not only can find a place but also can find buyers in the market while giving customers the "wow" moment when they meet the product. Kansei Engineering is a proactive product development methodology that translates customers' subjective criteria into concrete product parameters, allowing innovative solutions to be developed systematically.

Kansei engineering is not only a catalyst used in new product development. It is also an effective tool that can be used easily on the improvement of existing products (Schütte et al., 2004: 214). That is the reason why Kansei engineering in present is more important than the Kansei engineering in the past.

Kansei engineering is a methodology which consists of different methods and tools from different disciplines. So, why KE combines different disciplines? As the outcome of Kansei engineering is design, Engineering and Ergonomics; as it involves the detection and analysis of perceptions and emotions, Psychology and Neurology; as it includes statistical analysis, Statistics and Mathematics; and finally, as its consequences affect individuals and societies, Sociology and Economics are used in Kansei engineering. (Marco-Almagro & Tort-Martorell, 2011: 233)

The important point here is instead of developing completely new theories and tools, Kansei engineering works as a bridge between different scientific disciplines and uses suitable tools of these disciplines for forming new methods (Schütte et al., 2004: 216). Kansei engineering combines quantitative and qualitative methods in the studies. Due to the subjectivity of perceptions and feelings, studies such as focus groups and interviews are frequently used in the data collection. In the data synthesis/analysis, multivariate data analysis techniques like Principal Component Analysis, Cluster Analysis, Factor Analysis, Quantification Theory Type I, II, III, and Multinomial Regression Analysis are used.

According to Nagamachi, Kansei engineering studies should answer four questions:

1. How to catch the Kansei about a product?
2. How to obtain product attributes from the customers' Kansei?
3. How to create Kansei engineering system in an ergonomic way?
4. How to adapt products according to the preferences of societies and people? (Nagamachi, 1995: 4)

The ability to answer these questions is highly related to whether the studies are successful or not. While the studies that can capture the feelings and thoughts of the people about the product, determine the critical properties of the product, establish a system that can analyze the product features and consumers' Kansei efficiently, and finally transform the output of this system into a product considered as successful, the studies that are lacking even in one step may seem as unsuccessful in terms of results.

2.3 HISTORICAL DEVELOPMENT OF KANSEI ENGINEERING

Originally a psychologist and industrial engineer, Dr. Mitsuo Nagamachi started to provide consultancy services to variety of Japanese manufacturing companies after obtaining a PhD in Psychology at Hiroshima University. The companies that he has given consultancy were automotive and technology giants such as Toyota, Nissan, Mazda, Honda, Sharp, Matsushita (then become Panasonic) etc. While providing consultancy to these companies, he focused on the question of "is it possible to produce products based on people's perceptions and feelings?" and started on studying Kansei engineering at Hiroshima University in 1970 (Nagamachi, 2011: 9). He then presented KE as "consumer-oriented product development method in order to realize products' best fit to customer needs" (Nagamachi, 2008: 290).

Although the foundation of Kansei engineering studies were in the 1970s, Kenichi Yamamoto, Past Chairman of the Mazda Motors, was first used the term "Kansei Engineering" at the University of Michigan in 1986 as an effective approach that can be used for cars to contribute to culture. Moreover, Kansei Research Center was established for the production of the passenger car named "Persona" at Mazda's Yokohama Research Center.

In 1995, Nagamachi presented his seminal paper "Kansei Engineering: A New Ergonomic Consumer-Oriented Technology for Product Development" published in Applied Ergonomics Journal with the Academy, and it is considered as the entering of Kansei Engineering to the literature.

Mitsuo Nagamachi hosted the first Japan-Korea Kansei Engineering Symposium: Consumer-Oriented Product Development Technology in 1997. In 1998, he founded the Japanese Society of Kansei Engineering together with Japanese researchers (Nagamachi, 2011: 11).

Kansei engineering is also developing rapidly in Europe. Established in Linköping during the International Conference on Kansei Engineering and Emotional Research (KEER 2014) in 2014, the European Kansei Group (EKG) has been organizing and promoting KEER conferences since its establishment. Organizing its own biennial meetings (European Symposium on Kansei) in Europe since 2017, EKG aims to expand its network all over Europe in order to promote Kansei in the industry and academia (European Kansei Group, 2020).

Today, Kansei engineering is a multidisciplinary product development methodology spread around the World. With this methodology, dozens of product / service designs have made and many of them have taken their place in the market by completing their production processes.

2.4 TYPES OF KANSEI ENGINEERING

Eight types of Kansei Engineering have been developed to be used in the studies. Although their tools are different, their goals, paths and results are the same, because all these types are derived from the first type. For this reason, all types have similarities. This frees the researcher to choose the appropriate type depending on his study, time, and goals. Table 2 lists the types of Kansei Engineering with their brief explanation and the system each created. These types will be explained one-by-one in the following sections.

Table 2: Types of Kansei Engineering

Type	Name	Explanation	System created with the type
I	Category Classification	Dividing the target product concept into sub-concepts and translating into design features	Wacoal's Good Up Bra Design (Xue et al., 2011: 97-103)
II	KE System	Computer aided version of the first type. which includes databases and inference engine to transform consumers' perceptions and feelings into design elements.	Entrance Door Kansei Engineering System (EDKES) (Nagamachi & Lokman, 2016: 89-92)
III	KE Modeling	It functions as Type 2. This type uses mathematical modeling used, which overcomes fuzzy logic to create machine intelligence.	Word Image Diagnosis Fuzzy Expert System (WIDIAS) (Nagamachi& Matsubara, 1992: 845-846)
IV	Hybrid KE	It includes two stages of KE, forward and backward. The FKES ends with the creation of	Human Living System (HULIS)

		design elements, while the BKES does a Kansei evaluation from the design element.	Fashion Image System (FAIMS) (Nagamachi & Lokman, 2016: 85-89)
V	Virtual KE	By using virtual reality techniques, this type allows consumer to test products in the virtual world.	Custom Kitchen Kansei Engineering (ViVA System) (Enomoto, Nagamachi, Nomura, & Sawada, 1993)
VI	Collaborative KE	It is the type that allows designers or consumers in different locations to work together on the project through network.	Internet Kansei Designing System (IKDS) (Nishino & Nagamachi, 1999)
VII	Concurrent KE	People selected from different departments of a company works together to make Kansei evaluation and analysis.	Milbon's Shampoo Bottle Design (Nagamachi, 2002: 289-294)
VIII	Rough Set KE	It is considered the best method because it facilitates the analysis of uncertain and unpredictable data. It is the type that creates decision rules in the form of If-Then and also accepts nonlinear properties as independent.	Beer Can Design (Nagamachi, 2006: 27-37)

Source: Author's creation inspired by Lokman, 2010: 5-6

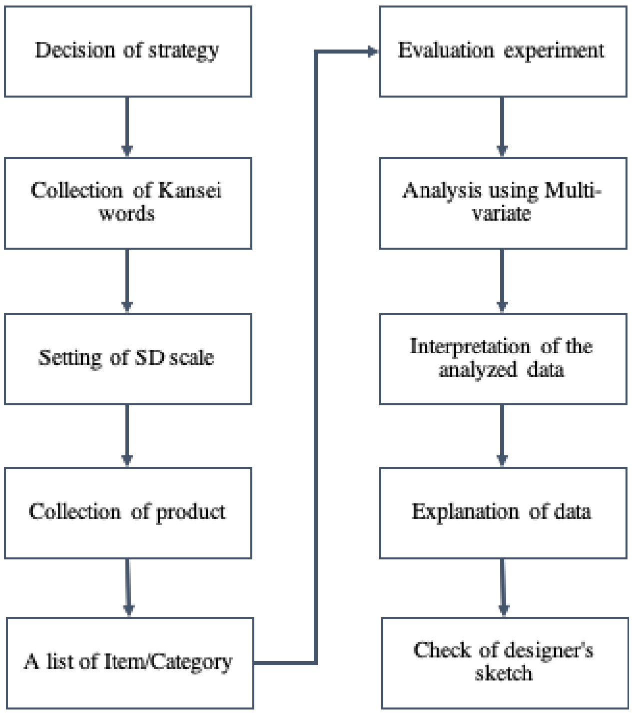
2.4.1 Kansei Engineering Type I – Category Classification

Kansei Engineering (KE) Type I is the easiest type to apply and understand. All other types are derived from this type. Therefore, understanding this type provides great facility to the researcher in applying other types.

In general, we can define Kansei Engineering Type 1 as a process which looks like a tree structure extending from the zero-level concept to the nth-level sub-concept. The zero-level concept is the strategic concept of the study and is also called the top concept. The main target of the product to be produced at this level is taken as basis. Then this concept is divided into a 1st-level sub-concept and the product target is detailed. This classification continues up to the nth level. The final structuring has a hierarchical order (Nagamachi, 2008: 291-292).

The stage mentioned above constitutes the first stage of the process, which is schematized in Figure 5. KE Type I process continues after the Kansei team reaches the concepts that make the customer satisfaction the highest. In all other types of KE, the process follows roughly the same order except the category classification step. Kansei, who express customers' feelings and thoughts about the product, are collected, a semantic differential scale is prepared, and sample products are collected. Then, a list of product features is prepared, and a Kansei experiment is performed. After the statistical analysis of the experimental results, it is necessary to interpret and explain the analyzed data so that they become design criteria. Finally, the drawing of the designed product is presented to the customer.

Figure 5: Kansei Engineering Type I Procedure

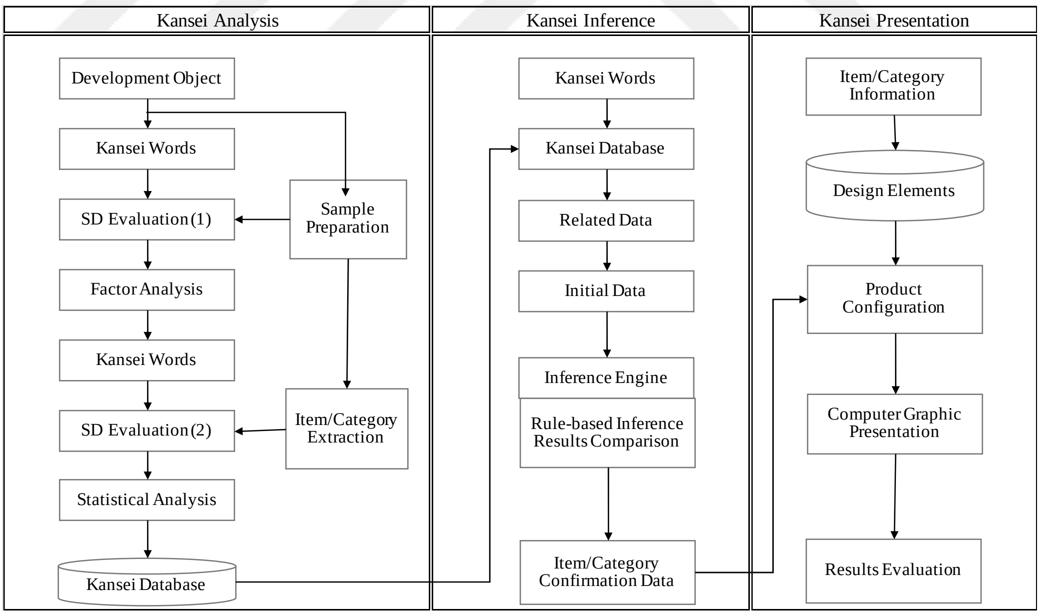


Source: Nagamachi, 2008: 291

2.4.2 Kansei Engineering Type II – KES

The Kansei Engineering System (KES) is the computer-aided version of Kansei engineering Type 1. This system helps the designer to work on the product and/or the consumer to choose the product. KES includes Kansei word database, product part database, knowledge-base, inference engine and system control (Nagamachi, 2006: 29). Figure 6 shows the structure of KES which has three sub-system as Kansei analysis, Kansei inference, and Kansei presentation (Yang et al.,1999: 462). We can define these three sub-systems as collection, translation, and presentation of the Kansei data. In the first subsystem, information about the product to be developed is collected and analyzed. In the second system, the Kansei words are processed with the information in the Kansei database created in the first system. After the results are compared in the inference engine, the created Item / Category information is moved to the third system and the design elements are mapped to the database and the results are shown.

Figure 6: Structure of Kansei Engineering System (KES)



Source: Yang et al., 1999: 462

2.4.3 Kansei Engineering Type III – KE Modelling

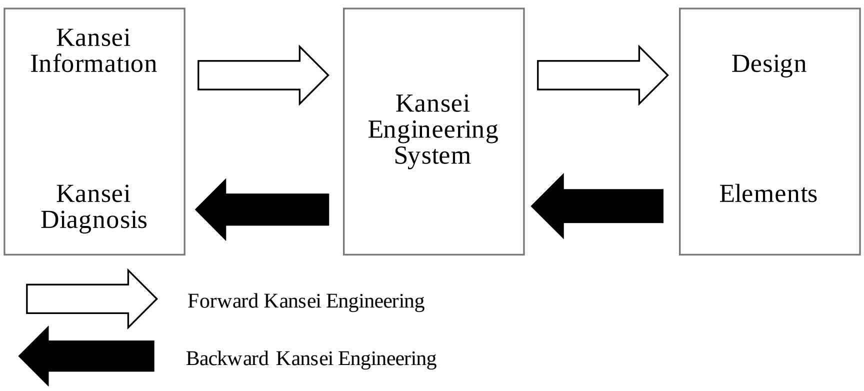
Kansei Engineering Type 3 works with a similar mechanism to Type 2. The difference is that instead of a rule-based system, a mathematical model is established (Nagamachi, 1995: 7). Mathematical Kansei engineering generally uses fuzzy logic to create machine intelligence (Lokman, 2010: 6).

As in all other types, this type starts with Kansei determination and attains the design features of the products. The difference in this type is that the relationship between input and output is expressed by establishing a mathematical model and at the end, coefficient value of this relationship is found (Nagamachi & Lokman, 2016: 37).

2.4.4 Kansei Engineering Type IV – Hybrid KE

The Hybrid Kansei Engineering System is generally a system that includes two Kansei engineering systems. In the Forward KE, it is ensured that the Kansei words used as input of the system are presented to the customers as design, while in the Backward KE, the design elements are used as inputs and according to the designer's ideas, the words and images are arranged (Nagamachi, 2006: 29). Figure 7 shows the basics of the hybrid KES and makes it easier to understand the system.

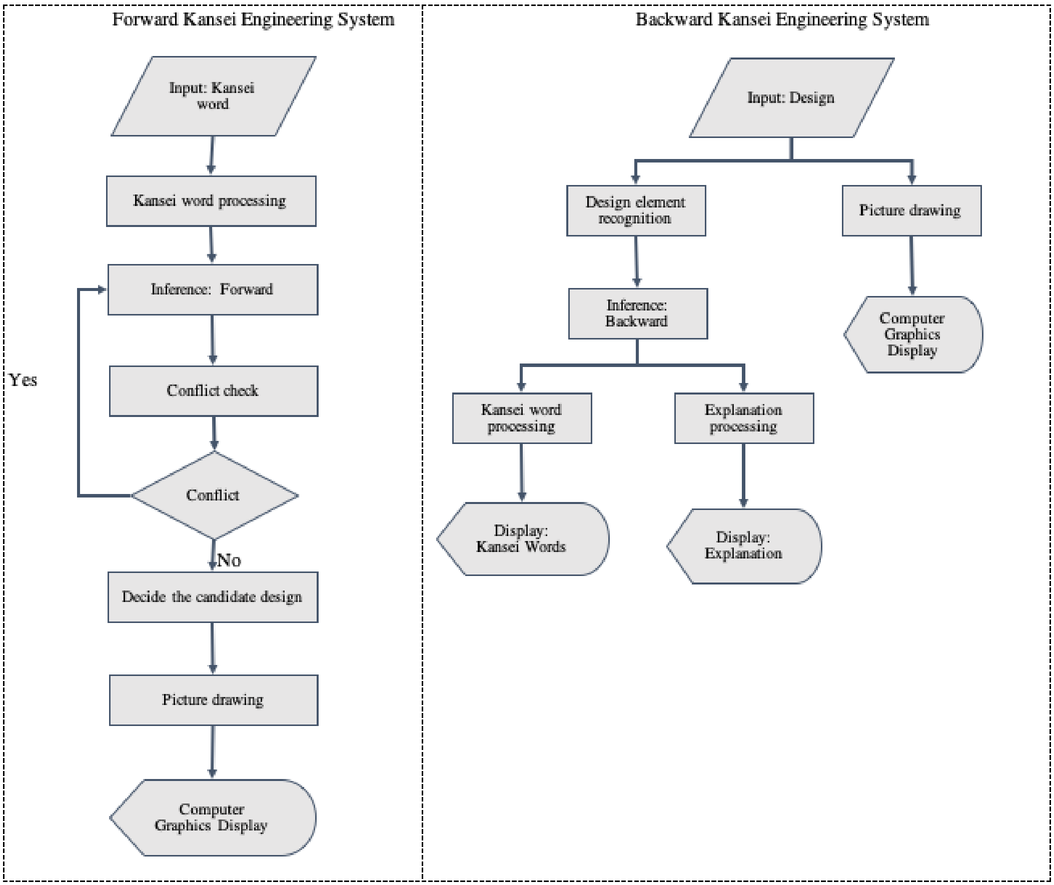
Figure 7: Hybrid KES Diagram



Source: Nagamachi, 1995: 9

Furthermore, Matsubara defines the structure of Hybrid Kansei Engineering System as shown in Figure 8. In this system, there are five databases as Kansei word database, knowledge base, image database, graphic database, and design database. The system also has four modules as Kansei word processing module, design processing module, inference module and system controller. In Forward KES, the consumer uses a Kansei word, and the system starts processing to find the relevant design alternative for presenting customer. In Backward KES, the designer puts the design element sets in the system, and system starts processing to define words and images about a product (Matsubara, 2011: 48).

Figure 8: System Flow of Hybrid KES



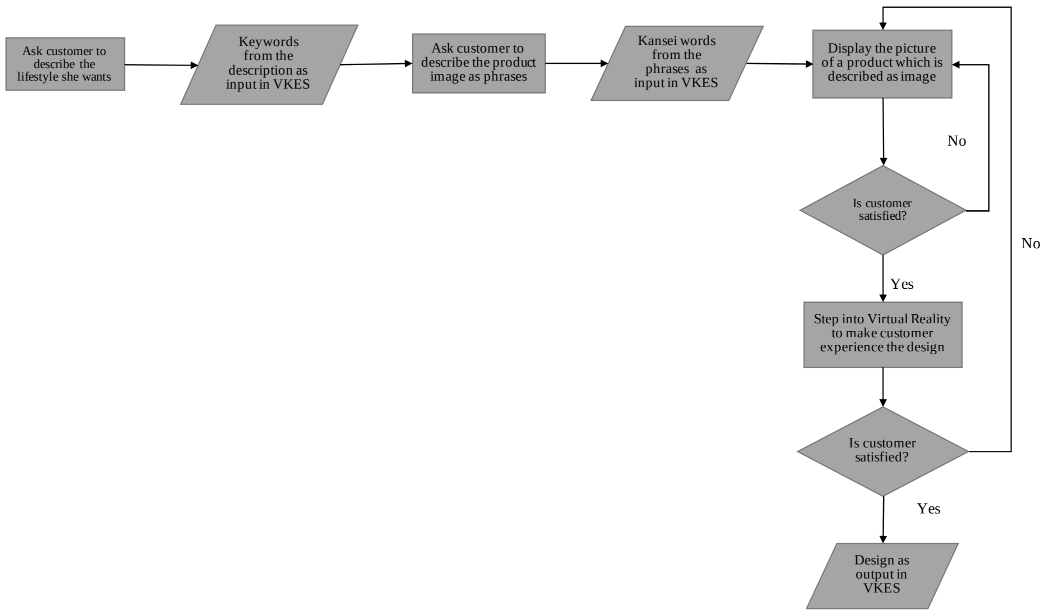
Source: Matsubara, 2011: 48

2.4.5 Kansei Engineering Type V – Virtual KE

Virtual Kansei Engineering System (VKES) is the advanced version of the Kansei Engineering System (KES – Type 2). In this version of KES, virtual reality technology and Kansei engineering are integrated. With this system, the virtual world prepared by the computer is provided to the customer to experience the simulated real world. In Kansei engineering studies, building, testing, and modifying products such as houses, and cars are demanding and very costly. However, creating products with the VKES only needs computer knowledge and time. The most important feature of this type is that it allows the customer to experience the product directly. In this way, the customer is directly involved in the design process and helps to find the product that satisfies her and matches the image in her mind (Nagamachi & Lokman, 2016: 107-113)

Figure 9 shows the flow chart of the Virtual Kansei Engineering System. In this system, Kansei engineering team asks the customer to describe her lifestyle to dream of. The keywords taken from this definition are processed into the system as input. Then, the customer is asked to define the image of the product she wants. After the words taken from this definition are processed into the system as input, the design alternative that matches the inputs in the system is shown to the customer as a picture. If the customer is satisfied, the process of experiencing the product in virtual reality begins. The customer can see the product from every angle and detect similarities and differences with the product she envisioned. If customer is satisfied with the design, the design shown is processed as output and the physical production process begins.

Figure 9: Flow chart of Virtual Kansei Engineering System (VKES)



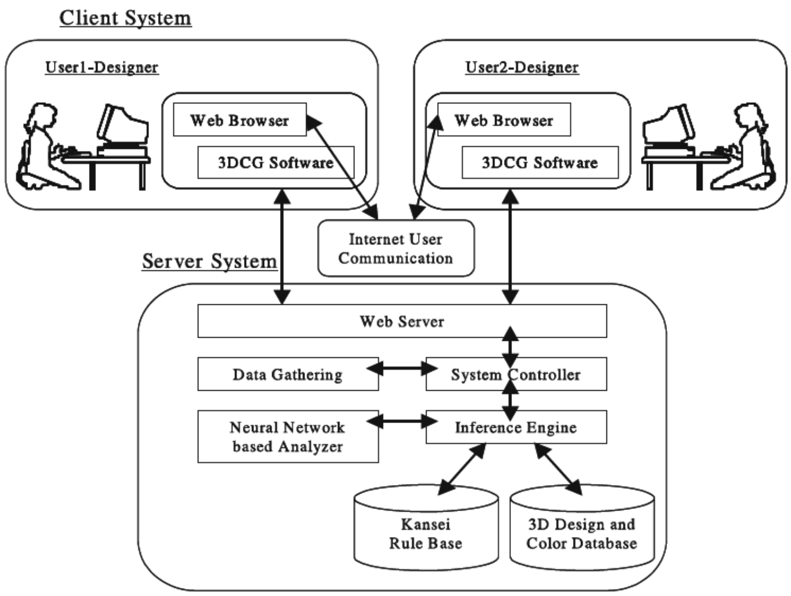
Source: Author’s creation (Inspired from Nagamachi & Lokman, 2016: 107-115)

2.4.6 Kansei Engineering Type VI – Collaborative KE

Collaborative Kansei engineering, an Internet-supported Kansei engineering system, is a type that aims to bring customers’ and designers’ point of view together with a smart groupware designing system. This system includes all Kansei databases and allows people from different positions, different disciplines, or countries to work on the same Kansei study.

Figure 10 shows the schema of Collaborative KE. In cases where the designer and the customer work together in the collaborative KE system, the product development success of the designer increases, and the customer can reach the desired product more easily. In this type of KE, people can design on the same screen, edit the design, and watch each other's screens. The system also allows people to communicate with voice. As a result, collaborative Kansei engineering has advantages such as shortening the new product development process, facilitating the generation of ideas, and increasing work efficiency (Nagamachi, 2006: 31; Schütte, 2002: 33).

Figure 10: Collaborative Kansei Designing System



Source: Nagamachi, 2006: 31

2.4.7 Kansei Engineering Type VII – Concurrent KE

In Concurrent Kansei engineering, employees in different positions and from different departments work on the same Kansei study. They complete the Kansei process and analysis of the study as Kansei engineering team. This type of KE allows KE team to achieve an integrated result in terms of ergonomics, quality, marketing, sales, and engineering (Lokman, 2010: 6). In addition, the opinions of experts from other relevant departments can also be obtained for the product being developed. That’s why applying Concurrent Kansei Engineering functions as a decision support system.

2.4.8 Kansei Engineering Type VIII – Rough Set KE

Statistical analysis techniques like principal component analysis, factor analysis, cluster analysis and multiple regression analysis are generally used in Kansei engineering studies. Kansei words that consist of feelings, emotions and perceptions of customers used in the studies may have non-linear features, which makes it unsuitable to use these techniques. In the case of non-normal distributions, techniques such as Neural Networks and Generic Algorithm etc. were used (Nagamachi, 2006: 35).

The Rough Set Theory developed by Z. Pawlak (Pawlak, 1991) provides great convenience in Kansei engineering studies as it can deal with complex data such as Kansei, regardless of whether the data is linear or not. This theory is based on Nishino's model, which applies upper and lower approximation that are relying on decision rules to Kansei data. With the lower and upper approximation, a solution range that includes both certain and uncertain solutions is added to the Kansei design (Nagamachi, 2006: 35; Nishino et al., 2005:177-219)

2.5 KANSEI ENGINEERING STUDIES IN THE LITERATURE

Kansei engineering studies can be used in the design of almost any product and service, and a wide variety of methods are used. Some of these studies are mentioned below.

Ishihara et al. (1995: 13-24) developed a self-organizing neural network to automate the analysis of the emotion-design relationship since the most used analysis technique -linear multiple regression- is a reliable but time/resource consuming and needs statistical expertise for feeling-design relationship analysis and rulemaking in KE expert systems. Using the ART1.5-SSS structure, the AKSYONN system is an easy-to-use system that requires less statistical expertise, can perform analysis and rule development without programming, and is also effective in small sample groups. In order to test the system, they made an experimental study on color consulting system to automate the relationship between Kansei and colors.

Horiguchi and Suetomi (1995: 25-37) argued that the driving simulator is a good tool for Kansei experiment, especially when designing a car. While the reasons of being a good tool are safety, flexibility, reproducibility, expandability, and observability, there are also some problems such as not capturing all emotions because the user experiences many emotions together while performing and getting away from reality because of two-dimensional experience of driving which is a three-dimensional activity. Then, the advanced driving simulator developed at Mazda Technical Research Center is explained in the rest of the study.

Yang et al. (1999: 459-471) presented the rule-based inference model, which includes five rules and two inference approaches (forward for reasoning design elements, backward for evaluating the results of comparison measurement). The model introduced includes the standardization, reasoning and comparison stages, and its main parameters are multiple correlation coefficients, partial correlation coefficients and category scores obtained by quantification theory type 1. The model was tested on the phone design and river view assessment in order to show the effect of the rules in the introduced model. As a result of the test, it was found that the model was effective in deciding the design elements for the selected Kansei words.

Nagamachi (1998) developed a successful Concurrent KE (Type 7) study. In this study, the unity of all departments of the company was ensured for the shampoo and treatment to be released by the cosmetics company Milbon and the top concept of the product was determined. Then, the 40-word SD scale prepared for 60 different container designs was presented to the university students for their evaluation, and a design in accordance with the concept of "soft and breezy (sara sara in Japanese)" was reached. Finally, the name of the series released is called 'Deesse's', which means 'as if Queen's' in Japanese (Nagamachi, 2002: 289-294).

Gong (2006: 533-548) discussed product development design philosophies and modeled fuzzy mathematic with the modified Hamming distance fuzzy set method, which is a simple and effective tool that engineers can use in sophisticated product design. To test the non-expert evaluation model, results were compared with real industrial application by conducting survey for new Apple and IBM-compatible computers within the same price range and technical specifications.

Aktar-Demirtaş et al. (2008: 17-31) wanted to include user perceptions and feelings in the kitchen fixture design process. In the study, the relationship between kitchen fixtures and Kansei words was modeled using Linear Regression and Ordered Logistic Regression analysis. Another result of the study is to find the design that maximizes the general preference scores of customers among the kitchen fixtures.

Castilla et al. (2017: 72-81) tried to identify design features that provide a positive affective response by placing the student at the center of the design process while most of the studies of designing university classrooms focused more on features such as lighting, sound, and temperature. As a result of the study where 918 students evaluated 30 classes in their own words, 6 different factors emerged. In addition, it was concluded that these factors are mainly about the functionality of working area, and the classroom's relationship with the external environment.

Vieira et al. (2017: 1-11) designed a user-centered rubber keypad using Kansei Engineering Type 2. Users were asked to evaluate the keypads determined by seven Kansei words to determine which keypad feature corresponds to which subjective perception. As a result, it has been revealed that the users can clearly distinguish the physical properties of the product and assign subjective properties to these features.

Hsiao et al. (2017: 284-302) suggested a KE approach that is an example for the Kansei design process in the service sector was applied to derive ideas for the development of the cross-border logistics service (CBLS). In this study, for the analysis of CBLS-related content, online text mining is used to determine the Kansei words for service items and CBLS, and Partial Least Squares (PLS) are used to analyze the relationships between customers' emotions and service elements of the CBLS. In the study, the results obtained using text mining and online content analysis were compared with the results obtained when the standard KE procedure was applied. It is concluded that the standard procedure is still a successful way of detecting customers ' emotions, but with online content analysis, customers' emotions are revealed more comprehensively.

Shieh et al. (2018: 31-42) proposed an approach to HKES that combines the methodologies of support vector regression (SVR) and multi-objective evolutionary approaches (MOEAs), in contrast to the HKES studies based on single-objective optimization. The approach creates predictive models by using support vector regression (SVR) in BKES and creates optimum design alternatives by using MOEAs in FKES. Although a case study of vase form design was conducted to test the approach, an optimal vase form design result could not be reached as the main purpose of the study was to compare three typical MOEAs.

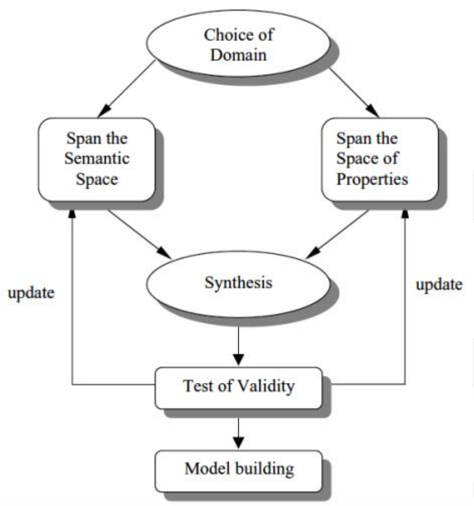
2.6 KANSEI ENGINEERING PROCESS

Kansei engineering is a long-running engineering process that extends from the determination of the product domain to the determination of product design features and the implementation of the design. As mentioned before, many different disciplines are used in the process. For the process to work successfully, the following four important questions need to be answered:

1. Who will the product serve / Who will use the product?
2. What do these people want / What are the people's Kansei?
3. How will people's Kansei's be turned into Kansei data?
4. How will these data be analyzed and how will the analyzed data turn into design attributes? (Nagamachi, 2011: 3)

In line with these questions, the Kansei engineering process visualized in Figure 11, is the most used figure in the literature as Kansei engineering process map. According to this figure, Kansei engineering process has 6 stages as determining the product domain, spanning the semantic space, spanning the space of product properties, synthesis, validity testing and model building. These stages will be detailed in this section.

Figure 11: Kansei Engineering Process



Source: Schütte et al., 2004: 219

2.6.1 Choosing the Product Domain

The first stage of the Kansei process where the product domain is determined. In this stage, target group is selected by performing market analysis or segmentation analysis. It is critical that the target group is clearly defined at this stage, as it will cause a change in the focused Kansei and product properties with the change to whom the product will appeal. For example, the new insurance policy of an insurance company appeals to university students has the properties that the policy which is addressing retirees cannot have as the expectations, desires, and feelings of these two target groups are completely different. For this reason, a clearly defined target group helps to base the work on the right foundations.

In addition to the importance of selecting the target group, it is also critical to decide whether to work on a new product or the development of an existing product.

Because representatives of the product also begin to gather during the domain selection stage and as representatives will be different for new and existing product. The product should also have been decided at the beginning of the study. While product samples are collected for existing products, computer drawings or virtual reality environments can be prepared, and also prototypes can be created for new products.

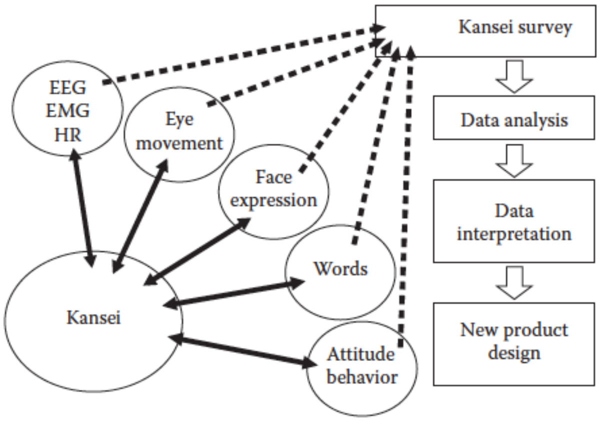
This shows that the KE process is completely shaped according to the Kansei product and the target group. Therefore, this stage is unique in all studies as different properties and Kansei are used for each product. Generally, there is no right method to use in this stage. To decide which method to use, it is crucial to know the study and the conditions.

2.6.2 Spanning the Semantic Space

In the previous stage, the product domain was determined. Next stage is where the semantic space is spanned in order to decide which Kansei words to use in line with the specified product domain. To summarize, at this stage, the maximum number of words that can be collected about the product is collected first. The aim here is not to miss any adjective or word that describes the product. The list is then narrowed down using qualitative or quantitative techniques. It is very important to establish a balance, as not narrowing list can cause problems as it prolongs the duration of the study and narrowing it too much may cause the loss of important words. Finally, the final list is prepared for the synthesis stage by using the semantic differential scale.

We can think of people's Kansei as a black box. That’s why how to detect and measure it is an important problem. Figure 12 shows the Kansei measurement techniques used today. It is possible to divide these techniques psychologically and physiologically. While heart rate, EMG and EEG are used in physiological techniques, words, eye movements, face expressions, attitudes and behaviors used in psychological techniques for measurement (Nagamachi, 2011: 4). Here it is necessary to dwell on a critical point. Since Kansei is subjective expressions collected for products, it is possible that (1) important statements representing the product cannot be collected, (2) statements that do not represent the product can be collected (Schütte et al., 2004: 220-222).

Figure 12: Spanning the Semantic Space



Source: Nagamachi, 2011: 4

Spanning the semantic space stage has three sub-stages in itself. As indicated in Figure 13, it is possible to elaborate these stages, which are divided into collecting, selecting, and compiling Kansei words as follows.

2.6.2.1 Collection of Kansei Words

At this point, the aim is to bring together the maximum number of words that can be collected using many different sources. These resources can be related literature, relevant Kansei studies, experienced users and experts, user manuals of the product, newspapers, magazines, ideas, and opinions. The word collection process continues until there are no more words to be added to the list, and usually a preliminary list of 50 to 600 words is prepared, depending on the product domain (Nagamachi, 1997; Schütte et al., 2004: 221).

2.6.2.2 Selection of Kansei Words

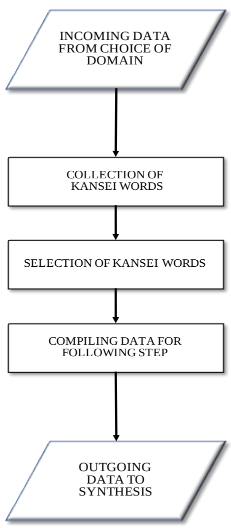
In this stage, rearrangement and selection are done by using word reduction techniques on the words of the preliminary list prepared at the collection stage before the synthesis stage. In fact, although using the first list is important in minimizing data loss, it makes it difficult to find subjects as the experiment of 600-words list will be completed in a long time. People who have accepted to be subjects may also lose consistency in their answers as they get bored towards the end of the study. This negatively affects the quality of the study. For this reason, it is useful to create a balanced list with minimum data loss and consistent answers when doing word reduction.

Word reduction can be accomplished using qualitative or quantitative methods. If the researcher will reduce the word with a qualitative method, Affinity Diagram can be used as an effective tool. By grouping a list with many words several times, the main list can be prepared. If the researcher will use a quantitative method, she can use cluster analysis and factor analysis. The only problem with using multivariate methods for word reduction is that it requires preliminary data collection. Although this can extend the duration of the study, it is more effective for the validity of the study.

2.6.2.3 Compiling the Kansei Words

In the last stage, Kansei words collected and selected in the previous stages are made to be analyzed with the Semantic Differential (SD) method. What is meant here is to make the list ready for experiment with the SD scale and to use it as an input to evaluate the product features determined simultaneously with this scale.

Figure 13*:* Flow of Spanning the Semantic Space

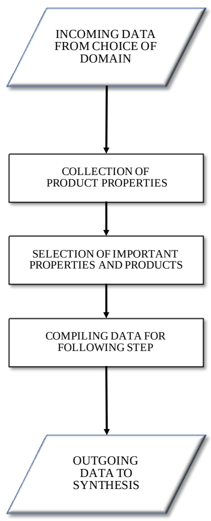


Source: Adapted from Schütte et al., 2004: 221

2.6.3 Spanning the Space of Product Properties

Spanning the space of product properties stage of Kansei engineering is shown in Figure 14. As can be seen in the figure, the stage consists of three basic steps. First, all the features related to the selected product are collected. Focus group work, literature review and expert opinion can be used here, as in the collection of Kansei words. Likewise, the basic features used in the product selection and purchasing processes can be determined with the audio recordings taken at the sales points. Then the designer identifies the most important product features without missing any features. It divides the features of the product into levels and is prepared for use in the study.

Figure 14: Flow of Spanning the Product Space



Source: Adapted from Schütte et al., 2004: 224

2.6.4 Synthesis

The synthesis stage constitutes the essence of the study in Kansei engineering studies. In this stage, the relationship between product attributes and Kansei words is established. Synthesis means that the Kansei words determined in the second stage and the product properties determined in the third stage are combined for collecting data. Briefly, it is the stage in which product samples, images, and drawings or virtual reality environments that can be determined as product representatives are evaluated with Kansei words placed on the semantic differential scale.

Survey is the most traditional but fastest way to collect data. In Kansei studies, product images or drawings can be evaluated as a survey on paper. Also, the same images and drawings can be evaluated on the computer. In this way, researcher can reach more people through the internet. In addition, product samples can be evaluated with an experiment conducted face-to-face. If a face-to-face experiment is selected for collecting data, the number of subjects attend the study will be less than the survey on paper and computer. However, the collected data may be more suitable for analysis. Finally, if we are talking about virtual reality, less people evaluate the product, but the consumer-oriented design will be done at the end of the VR process.

2.6.5 Validity Testing

In the fifth stage, incorrect or incomplete entries that cannot be used in the analysis among the collected data are cleaned. Then, the validity of SD scale is tested. Cronbach's Alpha is most used to test the reliability of the measurement tool and internal consistency of the Kansei words. For validity, the alpha coefficient is expected to be 0.70 and above (Özdamar, 1999).

2.6.6 Model Building

- Before the relationship modeling, the Kansei engineering data set can be defined as follows.Each kansei word from the semantic space are the dependent (response) variable which are ordinal scale integers (ranging from 1 to 5 for 5-point SD scale)
- Product attributes are the independent (explanatory) variables which are categorical factors that have at least two levels.

The relationship between Kansei words and product properties can be revealed using both qualitative and quantitative methods. Which method used depends entirely on the researcher, the study and the current conditions. Strengthening the relationship found by using more than one method is also a decision up to the researcher.

2.6.6.1 Qualitative Methods

Kansei Engineering Type I, which is called Category Classification, is the main qualitative method that can be used in the model building stage. In this type, the main product concept (zero-order concept) is determined at the beginning of the process, and then this concept is divided into sub-concepts until the design features are assigned. The most effective technique used in category classification is Affinity Diagram (K-J Method). The Affinity Diagram, a method created by Kawakati Jiro in the 1960s, allows an effective and creative organization of a large number of not grouped ideas, problems, and solutions (Dahlgaard et al., 2007: 124; Project Management, 2017). This technique is used to group the words revealed in Kansei studies and to associate these words with the concepts.

The important part at this stage is that the people prepare the diagram must be experts who have full knowledge of all the details of the study. Therefore, since the people dealing with the design of the product are usually the ones who know the best about a product, they are among the people who should be included in this study.

2.6.6.2 Quantitative Methods

Quantitative methods follow statistical procedures. Similarly, as qualitative methods, suitable quantitative method for the study can be determined based on the knowledge of the experts, conditions, and nature of the study. There are five main quantitative methods used in Kansei studies. Basically to express what they are used for, Principal Component Analysis is used to determine the structures of Kansei words and to group them; Cluster Analysis is used to group the sample of the study according to the similarities in their responses; Quantification Theory Type I is used to determine the relationship between design elements and Kansei words; Local Regression Method is used to show this relationship when there is a nonlinear relationship between Kansei words and design elements, and Correspondence Analysis or Quantification Theory Type III is used to visualize results by mapping variations in design elements (Nagamachi, 2011: 52-53). The methods used will be detailed in the Chapter Three.

CHAPTER THREE
METHODOLOGY

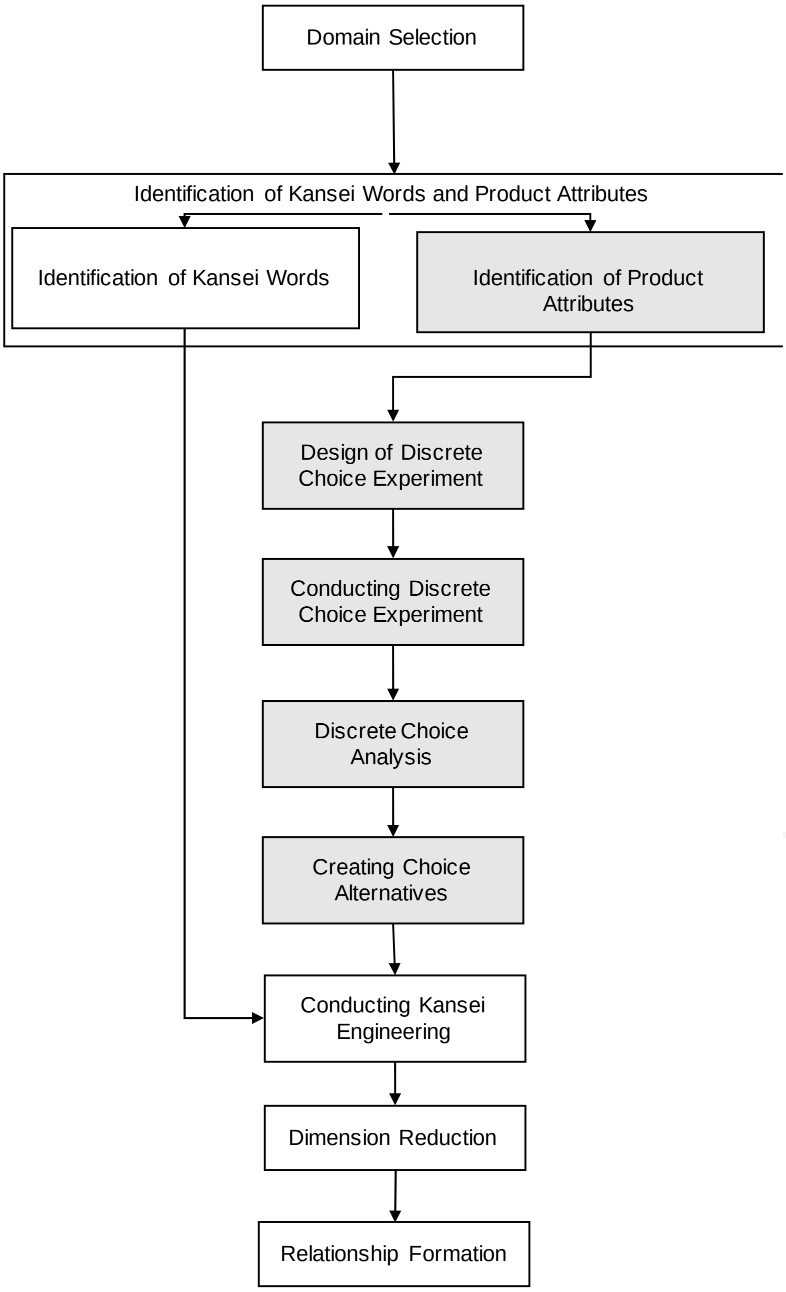
There is a wide variety of methods used for analyzing consumer behavior and product development in the literature. Quality Function Deployment, Kano model, Conjoint analysis and Kansei engineering are some of these methods. While QFD aims to include the customer's voice in the product development process by following the customer's steps, the Kano model aims to establish the bond between the customer and the product by understanding the customer's satisfaction. While developing the product that provides the highest utility by estimating the part worth utilities of the product attributes is carried out with Conjoint Analysis, Discrete Choice Experiment, as Conjoint Analysis, is a method used to evaluate hypothetical product alternatives and to identify the product alternative that maximizes utility. Unlike Conjoint Analysis, it is based on the principle of choosing among products instead of evaluating products by ranking or rating. Finally, Kansei engineering is used to transform the images in the people’s minds about the product into design alternatives. There are also studies in which these methods are used together. By using the methods together, it is aimed to reduce the limitations of the methods and to strengthen their effects.

The question of whether it is possible to develop a method that both determines the product alternative with the highest utility and measures the perceptions and feelings about that alternative has been influential in the formation of this thesis. As mentioned before, Schütte (2002: 44) said that while evaluating the product alternatives in the Conjoint analysis, people's Kansei are also indirectly measured. So, if the direct measurement of this indirect evaluation is provided, it will be possible to identify the alternative that maximizes the utilities of the people, while revealing the Kansei about the product.

In this thesis, a choice model strengthened by the integration of DCE, and Kansei Engineering is proposed. The Random Utility Theory (RUT), which is at the root of DCEs, assumes that utility functions used for modeling the choice behavior of individuals consist of both observable and unobservable parts. These unobservable parts consist of subjective criteria that customers evaluate when choosing products, apart from product attributes. Since the perceptions and feelings about the product are included in these subjective criteria, by integrating Kansei Engineering with DCE, the proposed model targets to get results closer to the actual choice behavior of the customers.

Stages of proposed model can be seen in Figure 15. In the model, first the product and target group are selected to define the domain of the study. Then, the Kansei words describing the product and the important attributes of the product are determined. Product alternatives are generated with various combinations of product attributes. The product alternatives generated are introduced to the participants from target group with a hypothetical scenario, and a survey is conducted in which the participants are asked to choose the ones they prefer most. After this stage, the collected survey data is analyzed and the part worth utilities of the attribute levels and the order of importance of the attributes are revealed. The process continues with the creating product alternatives according to the objective of the study. Then, the Kansei Engineering Experiment is designed using the Kansei words and the product alternatives created. After conducting the KE experiment, dimension reduction is applied for grouping Kansei words. Then, the relationship between Kansei words and product attributes is formed. All these stages are detailed in the following, will be also demonstrated on a course design study in Chapter Four.

Figure 15: A Customer-Oriented Choice Model



Source: Author's creation

3.1 DOMAIN SELECTION

The first stage of the proposed method is domain selection. Here, the product subject to study is determined first. The point to be considered when determining the product is whether the product is currently in the market or has not been produced yet. The presence of the product in the market is an important aspect that completely shapes the study. Because for the existing product, the presentation of alternatives is carried out using samples or product visuals, while for non-existing product, it may be necessary to create a hypothetical scenario and prepare prototypes or special drawings for the presentation.

Secondly, the target group of the study is determined. The target group is very critical for the attributes of the selected product to be used in the study. It was previously stated that the insurance company offers different insurance packages to students and retirees (See 2.6.1 Choosing the Product Domain). What is meant here is that even if the product selected for the study is the same, change in the target group may cause a change in the attributes of the product selected.

3.2 IDENTIFICATION OF KANSEI WORDS AND PRODUCT ATTRIBUTES

Identification of Kansei words and product attributes is the second stage of the proposed model. At this stage, firstly the semantic space and product attributes are spanned to reveal the attributes/characteristics and Kansei words of the selected product by using various qualitative methods. The main methods are conducting focus group study; taking expert opinion; reviewing the literature; investigating the relevant sections of the periodicals, newspapers, and magazines; making observations at the point of sales (PoS) and recording audio at PoS.

Recently, quantitative methods have also been used during the spanning of these spaces. The text mining method, which allows collecting and analyzing user comments, is more effective for collecting more words and attributes than qualitative methods. For example, Chiu and Lin (2018: 826-837) developed a method integrating text mining and Kansei Engineering and used the model in a case study for a road bike product to convert online customer reviews from amazon.com into design elements. This study is the first that integrates the two methods and its results revealed that text mining has the effect of accelerating the Kansei engineering process.

Depending on the product, a single method may be sufficient to reveal features and words, or multiple methods may be used. Which method or methods to use is left to the preference of the researcher.

3.2.1 Identification of Kansei Words

In order to identify Kansei words, the words express emotions, feelings, and perceptions about the selected domain are collected, selected, and prepared for data collection as defined in the following three steps.

3.2.1.1 Collection of Kansei Words (KW)

Collection of Kansei words is the first step of the identification. In this section, all words express the emotions, feelings, and perceptions can be collected using methods such as literature review, synthesizing the newspaper and magazines, taking expert opinion, and conducting focus group study etc. In order to avoid missing any words about the product, the suggestion here is collecting around 50 - 600 words. Then, this list is narrowed down and prepared for the survey in the following steps.

3.2.1.2 Selection of Kansei Words

Selection of Kansei words takes place by reducing and rearranging the words collected in the previous stage. Both quantitative and qualitative methods can be used while reducing the words. While affinity diagram is the leading qualitative method, clustering and factor analysis can be used for this purpose among quantitative methods.

The method chosen depends entirely on the researcher. For example, if quantitative methods are to be used, these multivariate analysis methods require preliminary data collection. In this case, the volunteer status of the participants who will be involved in the preliminary data collection process is critical. For a 300-word study, the preliminary data collection phase may take hours and word selection may not take place as desired because people have fatigue (Nagamachi & Lokman, 2016: 55-57). In summary, researchers can make a method decision by evaluating the situations such as their level of expertise, the number of words collected, and the volunteering of the people who will participate in the study.

Formally, the set of Kansei words selected in this step can be formulated as follows: $X = \{x_1, x_2, \ldots x_n, \ldots, x_N\}$ where N is the total number of words in the set. For example, if a 5-word Kansei list consists of the words creative, funny, interesting, enjoyable and engaging, then the list looks like below.

$$X = \{creative, funny, interesting, enjoyable, engaging\}$$

3.2.1.3 Compiling the Kansei Words

The last step of this stage is compiling the Kansei words, also called as the Semantic Differential (SD) scale development. Semantic differential is a method developed by Osgood that analyzes connotations in terms of evaluation words. A word pair with the antonym of an adjective is formed and placed on the Likert scale (between 3 to 11 points). Subjects are asked to evaluate the judgments given (Osgood & Suci, 1955: 325-338).

Here, 10 to 20 selected words are placed on the SD scale, so that they are prepared for the data collection.

In Kansei engineering, researchers usually prefer 5-point or 7-point scale in their study. Considering the studies on what should be done in the selection of scale points; studies have shown that the 3-point scale is not sufficient for reliability and validity as it has little differentiation, and regardless of how many categories they are designed with, the results of the 5-point and 9-point scale studies are almost the same. However, scales with more than 9-points are not needed because of not adding a distinctive difference to the study (Dawes, 2008: 61-77; Marco-Almagro, 2016: 236; Lawless et al., 2010: 4-12).

Semantic differential scaling in Kansei engineering studies does not consist of polished, antonyms (for example: good-bad, beautiful-ugly etc.) words as Osgood uses. It is generally recommended to use denial words (for example: good-not good, interesting-not interesting etc.). Using denial words instead of antonyms has two main reasons:

- Using antonyms can cause semantic confusion. Because not every word has perfect antonyms.
- Most of the frequency distribution is gathered on the positive word while analyzing the antonyms and the distribution moves away from normality. Such a distribution prevents most statistical analysis from being applied.

While applying the statistical tests, we need to choose parametric or non-parametric tests according to the distribution of data. As will be mentioned later, PCA and factor analysis are used in Kansei engineering studies. These techniques assume normality of data distribution. Therefore, if we use antonyms, we cannot perform Kansei analysis properly, because the data distribution will not be normal. By using denial words, the distribution becomes normal, and the problem disappears (Ishihara, 2011: 35-36).

3.2.2 Identification of Product and Service Attributes

Identification of product and service attributes is the parallel task of the second stage in the proposed model. To perform a good DCE, attributes and their levels must be defined correctly. Thus, it is necessary to evaluate all the attributes and characteristics for the selected product domain, without missing any of them, and to include the important ones as attributes. For this reason, it may be necessary to apply more than one method when determining product and service attributes.

For example, firstly, a focus group study can be carried out with randomly selected people from the target group of the study, and the data collected can be expanded by brainstorming with the experts, and finally, the determination of the final attributes and their levels can be completed by carrying out a study together with the expert and the researcher.

Furthermore, it is important choosing right people to be involved in determining the attributes and attribute levels. For example, suppose there is a distance of 3 km between a person's home and school. Let the person's way of going to school be an attribute. In this case, going by walking, car and bus are the correctly defined levels of this attribute, while going in by walking, ship and plane are incorrectly defined levels of this attribute. Among these misidentified levels, the person will not necessarily go to school by ship or plane, so she will choose to go by walking, and this will prevent researcher from accurately predicting one's choices. Therefore, people should have a good grasp of the basic concepts of the product and be able to predict the attributes that customers care about, so that the right attributes of the product are included, and right levels are determined in the study. Therefore, working with an expert team will make it easier to produce effective results.

Defining the attributes and levels in words that can be understood by everyone in the same way prevents inconsistent results (Tuncalı, 2007: 39; Yalçın, 2016: 30). That's why, attention should be paid to the choice of words.

3.3 DESIGN OF DISCRETE CHOICE EXPERIMENT

Design of DCEs can be performed manually or on a computer. However, nowadays, manual designs are almost never chosen. The reason for this is that design can be made quickly and effectively with computer programs. SPEED, SPSS, SAS and Sawtooth are the main softwares for designing DCEs. By the help of such softwares, researchers can create DCEs with balanced and orthogonal designs only by entering only the attributes and their levels to the program. Typical stages of a DCE design are briefly explained in this section.

3.3.1 Determining the Composition Rule

In the design of DCE, the composition rule is determined first. The choice is made between two compositional rules. The first of these, the additive model, involves calculating the utility of the product by summing the part worth utilities of the attributes. This rule evaluates only the main effects of attributes. The interaction effect, on the other hand, evaluates the product attributes that are related to each other. The part worth utilities determined according to the two- or three-way interactions are added together as in the additive model, and the utility of the product is calculated (Hair et al., 2007: 428-429).

3.3.2 Deciding the Presentation Method

Three presentation methods used in DCE studies were discussed in detail in the first chapter. By selection of these methods, it is decided how the alternatives will be shown to the participants, or in other words, how much information the created product alternatives will contain. The researcher will choose the method suitable for her study. Although the trade-off method was frequently used in the early years of traditional conjoint studies, it is not preferred today because it is not realistic. For this reason, one of the pairwise combination and full profile methods is preferred (Tuncalı, 2007: 42).

3.3.3 Using Prohibitions

The attribute levels not to be displayed together in choice sets can be prevented by using prohibitions in computer-aided experimental designs. However, in DCEs, the balance in the number of times levels is shown to respondents is very important for the design efficiency of the study. For this reason, the use of prohibition is generally not recommended in DCEs. Nevertheless, they can be used if there are some situations to using prohibitions is necessary and decrease in efficiency may be compromised (Sawtooth Software, 2021).

3.3.4 Fixed Tasks

In order to test the consistency of the answers of the participants in DCEs, fixed designed choice sets can be included in the experiment. These choice sets are created by the researchers and presented to all participants in the same way. Fixed designs are not included in the data analysis. They just control the consistency of the experiment by being evaluated separately (Sawtooth Software, 2021).

3.3.5 Generating Alternatives

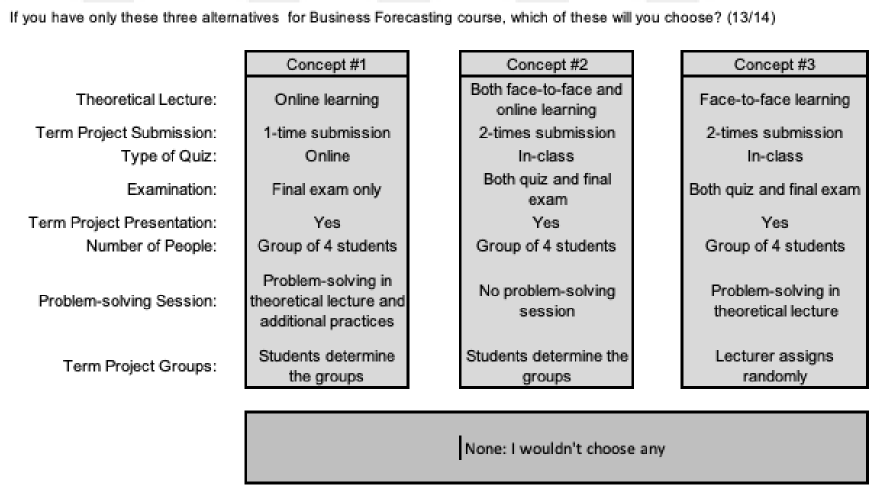
While generating alternatives, one of the full factorial or fractional factorial designs mentioned in the first chapter is preferred. Generally, fractional factorial designs are preferred because DCEs are usually performed for a large number of multi-level attributes where the use of full factorial design is not appropriate. During these designs, it is considered that the designs are balanced and orthogonal. Orthogonality means that the attributes are independent of each other, so that the main effects of each attribute can be measured separately, while balanced design means that each level of an attribute is displayed an equal number of times in the choice tasks (Hair et al., 2007: 408).

Today, researchers perform these designs quickly using developed software. Alternatives with design efficiency, in other words optimal designs, are created by simply entering the attributes and levels to the programs.

3.4 CONDUCTING DISCRETE CHOICE EXPERIMENT

Previously, DCE studies were mostly conducted face-to-face, using paper and pencil. However, computer programs allow both the design of the experiments and the implementation of the questionnaire to be carried out faster. Since it takes place on the internet, more people can be reached, and more choice sets can be included in the survey than face-to-face surveys. In addition, multimedia contents such as music, pictures and videos can be included in the survey. Figure 16 shows an example of online DCE choice task. The scenario is located in the upper part, the alternatives are in the middle and 'none option' is under of the image.

Figure 16: Online DCE Choice Task



DCEs simply consist of two steps. In the first step, a hypothetical scenario is presented to participants. This scenario is written for introduction of the product. So that, the participants have a good understanding of the environment and product they choose. In this scenario, the attributes of the product are explained in detail, allowing people to understand what is meant by the attribute names they have seen. Thus, the confusion will be minimized, and more consistent results are obtained. At the same time, what the product will be chosen for is also included in the scenario. For example, an experiment for a t-shirt and a t-shirt to wear for work will change people's choices. If the scope of the experiment needs to be narrowed in this way, it must be specified in the scenario. Thus, by presenting a scenario, people are allowed to make choices similar to those they make in the real environment.

Secondly, product alternatives created using product attributes are shown to the participants and they are asked to choose products in line with their preferences. DCEs include the 'none option'. In other words, participants have the right not to choose any alternative offered. Thus, it is ensured that the participants make choices similar to the choices they make in the real environment. The collected data with the experiment is analyzed in the next stage.

3.5 DISCRETE CHOICE ANALYSIS

Hierarchical Bayesian (HB) Estimation was used in the data analysis after the Discrete Choice Experiment. Since the HB method estimates the parameters in the mixed logit model and mixed logit is derived from the logit model, first the logit model will be mentioned in this section, and then the HB estimation will be explained after the mixed logit is introduced.

3.5.1 Logit

Decision maker n faces J alternatives. The utility obtained from alternative j of decision maker n is as follows (Train, 2009: 34-37).

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad (3.1)$$

The utility consists of two parts: observable part (V_{nj}) that researcher can estimate with certain parameters and the unobservable part (ε_{nj}), which the researcher assumes as random. The logit model assumes ε_{nj} is the independently, identically distributed (IID) extreme value. This distribution is also called the Gumbel distribution. Density of the unobservable part is $f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}}$ and the cumulative distribution is $F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}}$ (Train, 2009: 34-37).

The distribution of the difference between the two extreme values is logistic. Thus, if ε_{nj} and ε_{ni} are two extreme values, $\varepsilon *_{nji} = \varepsilon_{nj} - \varepsilon_{ni}$ follows the logistic distribution

$$F(\varepsilon *_{nji}) = \frac{e^{\varepsilon *_{nji}}}{1+e^{\varepsilon *_{nji}}} \quad (3.2)$$

The logistic distribution of error differences assumes that the errors are independent. Because the difference between extreme value and independent normal errors is indistinguishable. With independence, the unobserved utility for an alternative is not related to the unobserved utility of an alternative which means that the error of one alternative provides no information about the error of the other alternative (Train, 2009: 34-37).

The probability of the decision maker choosing alternative i

$$P_{ni} = Prob\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}\ \forall j \neq i\right)$$
$$= Prob(\varepsilon_{nj} < \varepsilon_{ni} + V_{ni} - V_{nj}\ \forall j \neq i) \qquad (3.3)$$

If ε_{ni} is given, it can be said that there is a cumulative distribution for each ε_{nj} evaluated in $\varepsilon_{ni} + V_{ni} - V_{nj}$. Since the errors are independent of each other, all distributions above $i \neq j$ are the product of the individual cumulative distribution and are represented as follows

$$P_{ni} \mid \varepsilon_{ni} = \prod_{i \neq j} e^{-e^{-(\varepsilon_{ni}+V_{ni}-V_{nj})}} \qquad (3.4)$$

Since ε_{ni} will not be given, the choice probability is the integral of all ε_{ni} values weighted by its own density.

$$P_{ni} = \int \prod_{i \neq j}(e^{-e^{-(\varepsilon_{ni}+V_{ni}-V_{nj})}})e^{-\varepsilon_{ni}}\, e^{-e^{-\varepsilon_{ni}}} d\varepsilon_{ni} \qquad (3.5)$$

The representative utilities specified linearly in the parameters are $V_{nj} = \beta'_{x_{nj}}$ and the vector of observed variables associated with alternative j is x_{nj}. So, the logit probability is found as follows.

$$P_{ni} = \frac{e^{\beta \prime x_{ni}}}{\sum_j e^{\beta \prime x_{ni}}} \qquad (3.6)$$

3.5.2 Mixed Logit

The utility function where all RUMs can be displayed is as follows.

$$U_{nj} = \alpha'_n z_{nj} \qquad (3.7)$$

where z_{nj} is variable associated with alternative j, and α follows any distribution of $f(\alpha)$.

The traditional notation shown in Equation (1) is obtained by letting $z'_{nj} = \langle x'_{nj}, d_j \rangle, \alpha' = \langle \beta'_n, \varepsilon_{nj} \rangle$ and $f(\alpha)$ as the joint density of β_n and $\varepsilon_{nj} \forall j$. The choice of persons can be fully determined, since U_{nj} will be known for each j conditional on the α. So, the conditional probability function is as follows (Train, 2009: 134-147).

$$q_{ni}(\alpha) = I(\alpha'_n z_{ni} > \alpha'_n z_{nj} \ \forall j \neq i) \quad (3.8)$$

where $I(.)$ Is the indicator of occurring the event, and takes value 1 if the event occurs, else 0.

According to the conditional probability, the probability takes either a value of zero or a value. This means that the choice of individuals conditionally on unknown random terms can be completely determined. The formula for the probability of an unconditional choice is as follows (Train, 2009: 134-147)

$$Q_{ni} = \int I\big(\alpha'_n z_{ni} > \alpha'_n z_{nj} \ \forall j \neq i\big) f(\alpha) d\alpha. \quad (3.9)$$

This unconditional choice probability is the integral of $q_{ni}(\alpha)$ over α, and it is as below

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta, \quad (3.10)$$

where $L_{ni}(\beta)$ is logit probability evaluated at parameters β, and is showed as below

$$L_{ni}(\beta) = \frac{e^{V_{ni}(\beta)}}{\sum_{j=1}^{J} e^{V_{nj}(\beta)}} \quad (3.11)$$

If utility is linear in β, then, $V_{ni}(\beta) = \beta' x_{ni}$.Therefore, the formula of mixed logit probability as follows:

$$P_{ni} = \int \Big(\frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}}\Big) f(\beta) d(\beta). \quad (3.12)$$

3.5.3 Hierarchical Bayesian Estimation

The Hierarchical Bayesian method is used to estimate the parameters in the mixed logit model. The HB is not a behavioral model. It is an estimation procedure used to estimate logit, GEV, probit, mixed logit, and all other discrete choice models. It is both used to estimate parameters without calculating choice probabilities and to show how individual-level parameters are explained by random taste variations in the model. The Bayesian method, which does not need to maximize any function, achieves properties such as consistency and efficiency more easily (Train, 2009: 299-305).

The reason why the method is called hierarchical is that there is a hierarchy in both parameters and prior. β_n is an individual-level parameter that shows the tastes of person n, and its distribution within the population is b as mean and W as variance. These b and W parameters are population-level parameters. The prior of each person's β_n is the density of β_n in the population, and the parameters of the prior also have the b as mean and the W as variance (Train, 2009: 299-305).

The utility of person n from alternative j in time period t is as follows

$$U_{njt} = \beta'_n x_{njt} + \varepsilon_{njt}, \qquad (3.13)$$

where β_n has normal distribution with mean b and variance W, and ε_{njt} is the IID extreme value. There is a prior on b as being normal with an unboundedly large variance. Also, there is a prior on W as being inverted Wishart with K degrees of freedom and scale matrix of I (Train, 2009: 299-305).

If $y'_n = \langle y_{n1}, \dots, y_{nT} \rangle$ is the chosen alternatives in all time periods for person n, and $Y = \langle y_1, \dots, y_N \rangle$ is the choices of the entire sample. Therefore, the probability of the observed choices of person n depending on β is

$$L(y_n|\beta) = \prod_t \left(\frac{e^{\beta' x_{ny_{nt}t}}}{\sum_j e^{\beta' x_{njt}}} \right) \qquad (3.14)$$

The probability not conditional on β is the integral of $L(y_n|\beta)$ over all β is

$$L(y_n \mid b, W) = \int L(y_n|\beta)\phi(\beta \mid b, W)d\beta \qquad (3.15)$$

where $\phi(\beta \mid b, W)$ is the normal density with mean b and variance W, and $L(y_n \mid b, W)$ is the mixed logit probability. The posterior distribution of b and W is

$$K(b, W \mid Y) \propto \prod_n L(y_n \mid b, W)k(b, W) \qquad (3.16)$$

In this distribution $K(b, W)$ is the prior on b and W, and it is possible to draw estimation directly by using Metropolis-Hasting (MH) algorithm. In each iteration of MH algorithm, $L(y_n \mid b, W)$ needs simulation for each n that would decelerate the calculation (Train, 2009: 299-305).

3.6 CREATING CHOICE ALTERNATIVES

The data collected in the first experiment were analyzed with Discrete Choice methods, and the order of importance of the determined product attributes and the part worth utilities of the attribute levels were revealed. At this stage, the researcher creates new products in line with the goal of the study by using the product attributes whose part worth utilities and importance are known.

In the creation of alternatives, a goal may be to uncover the effect of an attribute on perception and emotions. In such a case, alternatives with varying levels of the relevant attributes can be created.

If a goal is improving the design of a product, product alternatives can be created in the form of before and after, and the Kansei dimensions of the pre-design product and the post-design product can be examined.

The goal can also be to reveal the perceptions and feelings of the product that gives the highest utility. In such a case, only one product can be created for the next experiment.

Finally, product design can be done after removing the low utility levels or the attributes lagging in importance. This can be considered as a second experiment in which highly effective products are evaluated without evaluating the less effective properties.

3.7 CONDUCTING KANSEI ENGINEERING EXPERIMENT

The Kansei Engineering Experiment (KEE) is the second experimental study of the proposed model. In this experiment, the participants will evaluate the product alternatives with the determined Kansei words.

In KEE, product alternatives will be introduced with the presentation method selected according to the structure of the product. While simple presentation methods such as text and product cards are chosen for simple and easily recognizable products, multimedia contents, VR designs and prototypes can be used for non-existent and complex products.

The number of alternatives and Kansei words used varies according to the objective of the study. For example, if the researcher only wants to reveal the feelings and perceptions of the product alternative that gives highest utility, she can design a study that includes the evaluation of a single product with many Kansei words. On the contrary, if many alternatives will be used, it is recommended to keep the word list less than the previous example to produce consistent results from the participants.

The products introduced with the selected methods will be evaluated with the SD scale. For this reason, Kansei words are placed in the form of word pairs, usually on the 5- or 7-point SD scale. People evaluate the product by choosing whichever tail of the word pair they feel most proper with.

The data collected through the experiment will be analyzed with the methods introduced in the next section, and KW dimensions and relationship between Kansei words and product attributes will be revealed.

3.8 DATA ANALYSIS OF KANSEI ENGINEERING EXPERIMENT

The data analysis of the Kansei engineering experiment consists of two parts. In the first part, the dimensions of the data will be reduced and Kansei word structures will be revealed. Then, in the second part, the relationship between Kansei words and product attributes will be formed. The details of these data analysis methods are explained in detail in the following sections.

3.8.1 Dimension Reduction

Kansei engineering studies usually contain 8 to 20 words but there are also studies that contain more than 20 words. Since using so many variables will complicate the analysis, dimension reduction is the primary step of this stage. In addition, it is also important to find out which Kansei words are related to each other. Thus, researcher can have an idea about the structure of Kansei words. Therefore, to perform dimension reduction and reveal the structure of Kansei words, Factor Analysis (FA) and Principal Component Analysis (PCA) methods are used.

Factor Analysis aims to obtain fewer new variables (factors) from a data set consisting of p numerical variables and n observations with the minimum loss of information. These factors have statistically significant correlations between them. Because they are linear combinations of the original variables and are usually generated independently of each other. Although factor analysis is a traditional method, it is still preferred because it conforms to the principle of parsimony. The principle of parsimony refers to the most effective explanation of a multivariate system with as few dimensions as possible (Yıldırım & Alemdar, 2021).

The factor analysis model is as follows.

$$Z_j = a_{j1}f_1 + a_{j2}f_2 + \cdots + a_{jp}f_p + b_j u_j \qquad (3.17)$$

where,

$j = 1,2,\ldots,p$

$Z_j =$ j[th] standardized value

$f_j =$ j[th] factor

a_{jm} = loading of the j[th] variable on the m[th] factor

$u_j =$ residual factor

$b_j =$ residual factor coefficient

Considering that a_{jm} loading are the correlation values between each factor and variable, the variance explained by the factors can be obtained by summing the a_{jm}^2 values. This sum (h_j^2) is called common variance (communality). The part that cannot be explained by the factors is defined by the residual variance of b_j^2.

$$var(Z_j) = a_{j1}^2 + a_{j2}^2 + \cdots + a_{jm}^2 + b_j^2$$

$$h_j^2 = a_{j1}^2 + a_{j2}^2 + \cdots + a_{jp}^2$$

$$h_j^2 + b_j^2 = 1 \qquad (3.18)$$

In addition to FA, PCA can be also used for dimension reduction. Principal component analysis is one of the factoring techniques and helps to define multidimensional and very complex Kansei words with lower dimensions. According to Nagamachi (2011: 54), “the aim of PCA in Kansei engineering is to obtain a linear combination of variables that summarizes a n-dimensional distribution (e.g., n=80 for 80 Kansei words) using a lower-dimensional space.” Therefore, the reason that PCA is used in Kansei engineering is to make Kansei words understandable by using fewer dimensions. Making the data structure less dimensional by compressing its dimensions will facilitate its analysis.

There are some points where FA differs from PCA. In PCA, error and specific variance, whose sum is called unique variance, cannot be separated from each other in the calculation of variance. The main point that distinguishes PCA from classical factor analysis techniques is that while the error term is neglected in PCA in calculating the common factor variances of the variables, the error variance, which is not explained by the common factors and defined as residual variance in FA, is considered in the model. That is, while the total variance of p variables can be explained by the linear component of n common factors in PCA, there is another variance (error variance) that common factors cannot explain in FA. This distinguishes PCA from classical factor analysis, and it should be noted that with the reduction of unexplained variance in large data sets, the differences in the results of the two methods will decrease. In PCA, it is accepted that the variance for each variable is equal to 1.00. Accordingly, the total variance in the data matrix will be equal to the number of variables, and this will be equal to the sum of the eigenvalues of the factors (Büyüköztürk, 2002: 475; Kline, 1994: 36-40; Tabachnick & Fidell, 2001: 607-610)

Therefore, Tabachnick and Fidell (2001) recommend using FA if one is interested in theoretical solutions that are unique and not distorted by error variability. They also say that if an empirical summary of the dataset is desired, because of the use of equational operations and ease of computing, PCA should be preferred (Büyüköztürk, 2002: 475; Tabachnick & Fidell, 2001: 607-610). For the model proposed in this thesis, both methods were applied separately, and it was concluded that both methods could be used since there was no big difference between the outputs of the methods. Here, the choice is left to the preference of the researcher.

3.8.2 Relationship Formation

The final stage in the analysis of the Kansei engineering experiment is to reveal the relationship between Kansei words and product attributes. In this stage, it is determined which product attributes and Kansei words are associated with and what the direction of this relationship is. Quantification Theory Type I (QT1) and Partial Least Square Regression (PLS) methods are used for analysis.

3.8.2.1 Quantification Theory Type I (QT1)

The basis of Quantification Theory Type I is linear regression analysis. In a case where the value of variable y is explained using p number of variable x, let $x_1, x_2, \dots, x_p$ be the independent variables and y the dependent variable. The multiple linear regression model with three independent variables $(p = 3)$ is as follows (Nagamachi, 2011: 107-108).

$$y_i = a_1 x_{1i} + a_2 x_{2i} + a_3 x_{3i} + b \qquad (3.19)$$

where i is the number of alternative and $i = 1,2,3, \dots, m$

The purpose of this regression analysis is to find a_1, a_2, a_3 values, which are the weights of the x_1, x_2, x_3variables. Thus, it will be possible to find out how much each variable has an effect on dependent variable.

QT1 is used to reveal the relationship between Kansei words and product attributes in a direct and numerical way. QT1 is an advanced type of multiple linear regression analysis, which is effective in modeling the relationship mathematically. With QT1, categorical and qualitative variables such as design elements can also be included in the analysis (Komazawa & Hayashi, 1976; Schütte, 2002: 49). While multiple linear regression analysis deals with intervals or proportionally scaled variables, QT1 deals with both nominally scaled independent variables, intervals and proportionally scaled independent variables (Nagamachi, 2011: 113).

The relationship with QT1 is analyzed using dummy variables. The rule observed for coding design elements (product attributes) as dummy variables is as follows (Schütte, 2002: 49-52).

$$\delta_{i(jk)} = \begin{cases} 1, & If\ ith\ sample\ contains\ kth\ level\ of\ \ jth\ attribute \\ 0, & otherwise \end{cases} \qquad (3.20)$$

where,

$i =$ number of samples $(i = 1,2,3, \ldots, I)$

$j =$ number of attributes $(j = 1,2,3, \ldots, J)$

$k =$ number of levels for attribute j $(k = 1,2,3, \ldots, K_j)$

The value of the relationship between Kansei words and product attributes is as below.

$$Y_i = \sum_{j=1}^{J} \sum_{k=1}^{K} b_{jk}\, \delta_{i(jk)} \qquad (3.21)$$

where,

$Y_i =$ SD scale value for i^{th} Kansei word

b_{jk} = Correlation between i^{th} Kansei word and k^{th} level of j^{th} attribute

The purpose of QT1 as other multiple linear regression models is to estimate the b_{jk} value by minimizing the difference between the actual Y_i value and the estimated Y_i^* value. In other words, it is accurately predicting the relationship of attributes with Kansei words. This is achieved by the Least Squares Regression Method, which minimizes the error term (ε_i). In order to estimate the relationship by finding the b_{jk} value, the following formula must be solved (Schütte, 2002: 49-52).

$$\min L = \sum_{i=1}^{m} \varepsilon_i^2 = \sum_{i=1}^{m} (Y_i^* - Y_i)^2 = \sum_{i=1}^{m} \left(\sum_{j=1}^{J} \sum_{k=1}^{K_j} b_{jk}{}^* \delta_{i(jk)} - \sum_{j=1}^{J} \sum_{k=1}^{K_j} b_{jk} \delta_{i(jk)} \right)^2$$

$$\text{and } \frac{\partial L}{\partial b_{jk}} = 0 \qquad (3.22)$$

This formula needs to be solved separately for each Kansei word and coefficient, and the results of the relationship between attributes and KWs need to be found separately.

Although QT1 is often used to reveal relationships, it is impossible to analyze without dividing the variables if the number of samples is more than the number of design elements. Also, if there is multicollinearity between the variables, the analysis result is distorted. Thus, PLS method is used to solve these problems.

3.8.2.2 Partial Least Square Regression (PLS)

The Partial Least Squares (PLS) method is based on a study in the econometrics (Wold, 1966: 391-420). PLS is a good substitute for Multiple Linear Regression and Principal Component Analysis methods (Wold et al., 1984: 736).

PLS is used to find the fundamental relationships of the dependent and independent variables and is especially preferred when the number of independent variables is greater than the observations and there are multiple correlations between the variables. Unlike least squares regression, PLS can analyze multiple dependent variables with a single model. It is usually analyzed with computer aided statistical applications. For example, Minitab uses the NIPALS (Nonlinear Iterative Partial Least Squares) algorithm developed by H. Wold. This algorithm uses a method similar to PCA to extract the components with the maximum correlation between the dependent and independent variables (Minitab 18, 2019).

The PLS algorithm, adapted by Nagamachi from the work of Miyashita and Sasaki (1995), consists of 7 steps. Let vector y consists s number of dependent variables and vector x consists p-dimensional independent variables. Thus, the X matrix is s of x dimensional.

1. The covariance (w) of the x and y vectors is calculated. The w value acts as the eigenvector in PCA.

2. The latent variable (t_1) is revealed. This t_1 serves as the principal component score.

$$t_1 = \sum x_{ik} w_k = X w_1 \tag{3.23}$$

3. The relationship between the principal components values and the original values ($l_{11} l_{12}$ as principal component loading) is calculated.
4. The relationship between t_1 and y (q_1) is calculated as a result of simple regression analysis, where t_1 is the independent variable and y is the dependent variable.
5. The relationship between $x - t_1 - y$ is calculated.
6. The second latent variable (t_2) is found and the relationship $x - t_2 - y$ is revealed by repeating the five steps above. During this calculation, y takes the residual of the $x - t_1 - y$ model, and X takes the X residual of the $x - t_1 - y$ model obtained as below.

$$X_{new} = X - t_1 l_1^T \tag{3.24}$$

7. The relationship between two latent variables (t_1, t_2), y and x, is revealed.

CHAPTER FOUR
DEMONSTRATION OF THE MODEL

Higher education institutions are the cornerstones of the service sector that have to meet certain quality standards. These institutions must make continuous improvement to keep up with these standards. Universities that can design courses meet the demands of students and deliver these courses to students can easily achieve superiority over other universities. Universities that cannot meet the demands of students and therefore cannot satisfy them fall behind in the growing sector (Sheppard & Smith, 2016: 140). At this point, it is of great importance for universities to analyze students' preferences well and to design courses considering these preferences. In this chapter, how the model proposed in Chapter 3 works will be demonstrated by implementing the steps on university course design.

In the demonstration of the proposed method, the Business Forecasting course, which is taken as a compulsory course in the spring semester of the third year in the Business Department of the Faculty of Business Administration of Dokuz Eylül University, was chosen. The main reason for choosing the course is that the course is described as challenging by the students. Therefore, it is expected that improving the design of the course will directly increase the satisfaction of the students.

For the design of the Business Forecasting course, first of all, focus group study will be done. By doing so, the characteristics/attributes of the course and the Kansei related to the course will be gathered. These collected characteristics/attributes and words will be arranged by taking expert opinion. Then, product attributes and levels will be determined for the first experiment and course alternatives will be created. The course alternatives created will be presented to the students who take the course in the experiment. As a result of the experiment, the alternative that maximizes the utility of the students will be revealed and the partworth utilities provided by each course attribute will be estimated. After this point, the preparation of the second experiment will begin and firstly, the Kansei words collected and arranged in the focus group study will be reduced. Then, hypothetical course alternatives will be created according to first experiment. With the second experiment, students will be able to evaluate the hypothetical course alternatives corresponding to Kansei words on a semantic differential scale. Thus, the relationship between Kansei words and alternatives will be revealed. Finally, the design process of the course will be completed by using the words and the attributes that maximize the utility of the students.

4.1 DOMAIN SELECTION

As said before, Business Forecasting course is a compulsory course in Dokuz Eylül University Faculty of Business, Business Administration program. Students are obliged to take the course when they come to the second term of the third grade. The course is divided into two different sessions, theoretical and laboratory, and students have to attend these two sessions at different times on the same day or on different days. Students are also responsible for a term project that they will prepare as a group to reinforce the outcomes of the course.

By students, course was seen as challenging. The main reason for this is that for understanding the course clearly, advanced statistical knowledge will be needed. Students have taken the Basic Statistics course in the first year and did not take any supportive course before taking the Business Forecasting course. Therefore, since students encountered this course two years after taking the Basic Statistics course, they have difficulty in following the course. Thus, the Business Forecasting course was chosen in order to provide the students with the program objectives and outputs. Moreover, it is thought that designing student-oriented course will directly increase the satisfaction of the students.

Therefore, the application of the proposed model is planned to be done through the design of this course. The group determined as the domain of experimental studies are the students who took this course in the 2019-2020 Spring semester, which is the period when the thesis was written.

4.2 SPANNING SEMANTIC SPACE AND PRODUCT ATTRIBUTES

In this study, to determine the Kansei words and course attributes, the focus group study was conducted with students who are randomly selected and include the ones who successfully completed the course by taking the course for the first time or more than once in the previous years, and the ones who have failed the course last year and will take the course again this year. Although the group was chosen randomlDuring the focus group study, audio recording was taken with the consent of the students. These audio recordings were later transcribed to collect the words Kansei.

The study took one hour and at the end of the study, the following items were obtained.

- Main concepts of the course
- Course components - instructor, content, material
- Learning outcomes of the course
- The place / importance of the course in terms of student expectations about their departments
- First five emotions that come to mind about Business Forecasting course

4.3 IDENTIFICATION OF KANSEI WORDS AND COURSE ATTRIBUTES

In the identification stage, it is aimed to determine the course attributes and the Kansei words that describe the course. At this stage, data collected through focus group study were expanded by using the literature and conducting brainstorming session. Finally, the attributes and words to be used in the experiments were decided after taking expert opinion. All these stages will be detailed below.

4.3.1 Identification of Kansei Words

In order to determine the Kansei words, firstly, the focus group study was conducted. Before the focus group study started, the students were asked to write down the first five words that came to mind when talking about this lecture on a piece of paper. The words were later added to the KW list. The audio recording taken with the consent of the participants in the focus group study was transcribed, and the words related to the course were listed among the obtained data. Then, words were added to the list by using the literature. Finally, a brainstorming session with the lecturer of the course was done and the first Kansei words were revealed. The first list contains about 60 words. The words in this list were reduced using the Affinity Diagram and the following Kansei Words were determined as in Table 3.

Table 3: Kansei Words

(k_1) Abstract	Concrete
(k_2) Centralized	Decentralized
(k_3) Individualistic	Collaborative
(k_4) Not satisfactory	Satisfactory
(k_5) Basic	Advanced
(k_6) Not educational	Instructional
(k_7) Non-effective	Effective
(k_8) Non-interactive	Interactive
(k_9) Disorganized	Organized
(k_{10}) Non-analytical	Analytical

The set of Kansei word pairs is as follows.

KW= { (abstract, concrete),(centralized, decentralized),(individualistic, collaborative), (not satisfactory, satisfactory), (basic, advanced), (not educational, educational), (non-effective, effective), (non-interactive, interactive), (disorganized, organized), (non-analytical, analytical) }

The form of the words used in the experimental analysis is as in the formula below.

$$KW = \{(k_1\ ), (k_2\ ), (k_3\ ), (k_4\ ), (k\ _5), (k_6\ ), (k_7\ ), (k_8\ ), (k_9\ ), (k_{10})\}$$

4.3.2 Identification of Course Attributes

In order to determine the course attributes, the focus group study was carried out first. Then, the results were shared with the lecturer of the course. Thus, expert opinion was taken, and the data obtained through the study were arranged. While making this arrangement, the focus was on revealing the characteristics/attributes of the course that should be evaluated in the design process, in other words, the attributes that are thought to affect the utility. Table 4 shows the eight attributes that were determined as a result of the focus group study and expert opinion. These attributes can be evaluated under three main titles: lecture, examination, and term project. The attributes and their levels will be explained below.

There are two attributes under the title of lecture. These are the attributes about how the theoretical lecture will be handled and how the problem-solving session will take place. The theoretical lecture can only be done in class or online, or the resources can be accessed online while the theoretical lecture is done in class. The problem-solving session, on the other hand, may not be held at all, it can be done in the theoretical lecture, or in addition to the problem-solving session in the theoretical lecture, additional practices can be given.

In addition to the attributes about the lecture, there are two attributes under the title of examination. These are the attribute that include the existence of quiz and final exams, and the attribute about how to do the quiz. In the existence of quiz and final exams, students have three options: only a quiz, only a final exam, or both a quiz and a final exam can be done. For the second attribute, students have two options: the quiz can be done in class or online.

Finally, there are four attributes in the term project title. These attributes include the determination of the term project groups, the number of people in the groups, the term project submission, and the term project presentation. The students have two options in determining the groups of the term project: they can be assigned randomly by the lecturer of the course, or the students can determine the groups themselves. For the number of people in the groups, students will choose from three options: groups of 2, 4, or 6 students. During the term project submission, students can choose between submitting at once or submitting in two times, and lastly for the term project presentation they can choose whether to present a term project.

Table 4: Course Attributes and Attribute Levels

Attribute	Explanation	Levels
Theoretical lecture	How will the theoretical lecture be handled	▪ In-class ▪ Online ▪ Both in-class and online
Problem-solving session	How the problem-solving session will take place	▪ No problem solving session ▪ Problem solving in theoretical lecture ▪ Problem solving in theoretical lecture and additional practices
Examination	Which exams will take place	▪ Quiz only ▪ Final exam only ▪ Both quiz and final exam

Type of quiz	How will the quizzes be conducted	▪ In-class ▪ Online
Term project groups	How the project groups will be determined?	▪ Lecturer assigns randomly ▪ Students determine the groups
Number of people	How many people will the term project groups consists of	▪ Group of 2 students ▪ Group of 4 students ▪ Group of 6 students
Term project submission	How many times will term project be delivered	▪ 1-time submission ▪ 2-times submission
Term project presentation	Will there be a term project presentation	▪ No ▪ Yes

4.4 EXPERIMENTAL DESIGN

As mentioned before, in designing the experiment, the combination rule, the presentation method and the prohibitions to be used are determined and fixed design alternatives are created. Then selection alternatives are created. Details for this study are given below.

4.4.1 Composition Rule Determination

At this stage, the composition rule was decided first. The additive model consisting of the sum of the part worth utility values given to each attribute was used in this DCE. As can be seen in Table 4, there are 20 levels for 8 attributes in total for the design of the Business Forecasting course.

4.4.2 Prohibitions

Since the course of that term will be replaced by the alternative that maximizes the utility, the lecturer of the course did not find it appropriate to include some alternatives together. For this reason, two prohibitions were used in the study.

The first prohibition is among the attributes of theoretical lecture and problem-solving session. The case that there is no problem-solving session where theoretical lecture is handled online, and the case that theoretical lecture is handled face-to-face where there is a problem-solving session and additional practices given as assignments are not preferred by the lecturer for time-related reasons.

The second prohibition is among the attributes of examination and the number of term project people. The reason for this prohibition is generally for balancing the workload. Since it is not preferred that the term project group consists of 2 students in a situation where there will be both a quiz and a final exam, and it is also not preferred that the term project group consists of 6 students when there is only a quiz, a prohibition has been set so that these levels are not included together.

4.4.3 Fixed Task Generation

Two different fixed designed choice tasks were included in the study. These choice tasks are not used to estimate students' utility. Their job is to check the internal validity of the DCE. Fixed tasks created for the study are shown in Table 5 and Table 6.

4.4.4 Designing the Experiment

Experiment was designed in Sawtooth Software Lighthouse Studio v9.11.0 using the Choice-Based Conjoint method (Sawtooth Software, Inc., 2021). The details of experimental design are as follows.

Sawtooth Software, Inc. stated that it is normal for a typical DCE study to contain between 8 and 15 choice tasks (Sawtooth Software, 2021). In this study, a total of 14 selection tasks, 12 of which are random and 2 of which are fixed design, were used. Creation of 300 questionnaire versions were decided. Thus, 12x300=3600 course alternatives are randomly generated.

There are 3 different course alternatives (product concepts) in each choice task. The 'None' option is also included the study to support the authenticity. Students were given the chance not to choose any of the course alternatives shown in a choice task and this allows students to feel like they are making a choice in the real world.

As a result, students will have answered a total of 14 selection tasks with 3 course alternatives and 1 'none' option. At the end of the study, each student evaluated 14x3=52 course alternatives and made choices that maximized their own utility.

Table 5: Fixed Task I

	Concept #1	Concept #2	Concept #3
Theoretical Lecture:	Face-to-face learning	Online learning	Both face-to-face and online learning
Term Project Submission:	1-time submission	1-time submission	2-times submission
Type of Quiz:	In-class	Online	Online
Examination:	Quiz only	Final exam only	Quiz only
Term Project Presentation:	No	No	Yes
Number of People:	Group of 4 students	Group of 6 students	Group of 4 students
Problem-solving Session:	No problem-solving session	Problem-solving in theoretical lecture	No problem-solving session
Term Project Groups:	Students determine the groups	Students determine the groups	Lecturer assigns randomly

Table 6: Fixed Task II

	Concept #1	Concept #2	Concept #3
Theoretical Lecture:	Online learning	Both face-to-face and online learning	Face-to-face learning
Term Project Submission:	1-time submission	2-times submission	2-times submission
Type of Quiz:	Online	In-class	In-class
Examination:	Final exam only	Both quiz and final exam	Both quiz and final exam
Term Project Presentation:	Yes	Yes	Yes
Number of People:	Group of 4 students	Group of 4 students	Group of 4 students
Problem-solving Session:	Problem-solving in theoretical lecture and additional practices	No problem-solving session	Problem-solving in theoretical lecture
Term Project Groups:	Students determine the groups	Students determine the groups	Lecturer assigns randomly

4.5 CONDUCTING DISCRETE CHOICE EXPERIMENT

Discrete Choice Experiment have begun with directing students to a specific web page opened for this study. The experiment was performed at the end of the lesson while the students were in the classroom. The researcher explained the hypothetical scenario and how the experiment will be done to the students. The study was carried out in Turkish. An example of the experiment is shown in APPENDIX II.

Data collection in the study consists of two sections. In the first section, demographic data including the characteristics of the students are collected. In the second section, the students are asked to choose the ones they prefer most from the choice sets in line with the hypothetical scenario given.

Determining the demographic characteristics of the students is important in understanding whether there is a change in course preferences for various groups. For this reason, 6 different questions were asked to the students. The demographic data collection process was completed by asking students' gender, department preference rankings, classes, and GPA. In addition to these questions, questions were asked to learn when they took the course and whether they took a course in QMT major or not.

In the second part, 14 choice tasks, 12 of which are random and 2 of which are fixed design, were directed to the students. In total, they are asked to choose the most preferred among 52 course alternatives. The data collected at the end of the experiment will be analyzed in the next section and the results will be given.

4.6 DISCRETE CHOICE ANALYSIS

Experimental data of 78 participants were analyzed using Sawtooth Software Lighthouse Studio package program (Sawtooth Software, Inc., 2021). Results of analysis will be given below.

4.6.1 Analysis of Main Effects

Results for main effects were obtained using Lighthouse Studio. In the analysis of the data, firstly, the method called 'Counting Analysis' was used. With this method, the results were obtained by dividing the number of choices of the course alternative with a certain level of an attribute by the total course alternatives. Whether there is a significant difference between the levels of the 8 attributes selected was also analyzed for 99% significance level. The results for all attributes and attribute levels are as in Table 7.

Considering whether there is a significant difference between the levels for the theoretical lecture.

"H_0: There is no significant difference between the levels in the theoretical lecture attribute."

“H_1: There is a significant difference between the levels in the theoretical course attribute.”

the hypotheses above were established. At 99% significance level and the degree of freedom $d = number\ of\ levels\ within\ the\ attribute - 1 = 3 - 1 = 2$, the chi-square critical value is found as $\chi^2_{0.99} = 9.21$. Since the chi-square value obtained is $\chi^2 = 11.689 > \chi^2_{0.99} = 9.21$, the H_0 is rejected. This shows that there is a significant difference between the levels of the theoretical lecture attribute. The results show that students prefer the option where the theoretical lecture is handled both face-to-face and online learning.

Considering whether there is a significant difference between the levels for the problem-solving session.

Since the degree of freedom $d = 2$ for a three-level attribute, it has a chi-square value $\chi^2_{0.99} = 9.21$. The value obtained for this attribute $\chi^2 = 10.101 > \chi^2_{0.99} = 9.21$ means that $H_0$is rejected. Therefore, there is a significant difference between the levels in the problem-solving session attribute. The most preferred level by the students for this attribute is the problem-solving session in the theoretical lecture. The proportion of this level is 20.6% of problem-solving session attribute.

Considering whether there is a significant difference between the levels for the term project groups.

Determining term project groups is a two-level attribute. The chi-square value for this attribute is $\chi^2 = 28.608$. Since the degrees of freedom for the two levels are $d = 1$, the chi-square value is $\chi^2_{0.99} = 6.635$. So, as $\chi^2 = 28.608 > \chi^2_{0.99} = 6.635$, H_0 is rejected, andt is found that there is a significant difference between the levels for the attribute of term project groups. The students want to determine the groups by themselves. The choice rate for this level was found to be 22%.

Considering whether there is a significant difference between the levels for the number of people.

The chi-square value for the number of students in term project groups attribute is $\chi^2 = 17.137$. Since there are three levels for this attribute, the chi-square value for $d = 3 - 1 = 2$ is $\chi^2_{0.99} = 9.21$. Since $\chi^2 = 17.137 > \chi^2_{0.99} = 9.21$, H_0 hypothesis is rejected. In this case, there is a significant difference between the levels for the number of students in the groups. For this attribute, the alternatives with groups of two students were preferred at most by the students with 21.2%.

Considering whether there is a significant difference between the levels for the term project presentation.

The chi-square value obtained for the term project presentation was found as $\chi^2 = 12.342$. Since the chi-square value is $\chi^2_{0.99} = 6.635 < \chi^2 = 12.342$, the H_0 hypothesis is rejected. This indicates that there is a significant difference between the levels of the term project presentation attribute. Students mostly preferred alternatives without term project presentation. The choice rate of the level is 20.8%.

Considering whether there is a significant difference between the levels for the term project submission.

Since the chi-square value obtained for the term project submission is $\chi^2 = 1.543$ and the chi-square value for $d = 1$ is $\chi^2_{0.99} = 6.635$, the H_0 hypothesis cannot be rejected because $\chi^2 = 1.543 < \chi^2_{0.99} = 6.635$. In this case, there is no significant difference between the levels for the term project submission.

Considering whether there is a significant difference between the levels for the examination.

The chi-square value for the examination was found to be $\chi^2 = 63.816$. As $\chi^2 = 63.816 > \chi^2_{0.99} = 9.21$, the H_0 hypothesis is rejected and there is a significant difference between the levels for examination. Alternatives with quiz only were mostly preferred. The choice rate for quiz-only level was found to be 27.4%.

Considering whether there is a significant difference between the levels for the type of quiz.

H_0 hypothesis for the type of quiz attribute cannot be rejected since the chi-square value of this attribute is $\chi^2 = 0.143 < \chi^2_{0.99} = 6.635$. This means that there is no significant difference between whether the quiz is in-class or online.

Table 7: Results Obtained by Counting Analysis

Theoretical Lecture	Attribute Levels	Face to face learning	0,133	Term Project Presentation	Attribute Levels	No	0,208
		Online learning	0,162			Yes	0,151
		Both face to face and online learning	0,204				
	Results	Within Att. Chi-Square	11,689		Results	Within Att. Chi-Square	12,342
		D.F.	2			D.F.	1
		Significance	p < .01			Significance	p < .01
Problem Solving Session	Attribute Levels	No problem-solving session	0,145	Term Project Submission	Attribute Levels	1-time submission	0,189
		Problem solving in theoretical lecture	0,206			2-times submission	0,169
		Problem solving in theoretical lecture and additional practices	0,187				
	Results	Within Att. Chi-Square	10,101		Results	Within Att. Chi-Square	1,543
		D.F.	2			D.F.	1
		Significance	p < .01			Significance	not sig
Term Project Groups	Attribute Levels	Lecturer assigns randomly	0,134	Examination	Attribute Levels	Quiz only	0,274
		Students determine the groups	0,220			Final exam only	0,166
						Both quiz and final exam	0,108
	Results	Within Att. Chi-Square	28,608		Results	Within Att. Chi-Square	63,816
		D.F.	1			D.F.	2
		Significance	p < .01			Significance	p < .01
Number of people	Attribute Levels	Group of 2 students	0,212	Type of Quiz	Attribute Levels	In-class	0,182
		Group of 4 students	0,192			Online	0,176
		Group of 6 students	0,130				
	Results	Within Att. Chi-Square	17,137		Results	Within Att. Chi-Square	0,143
		D.F.	2			D.F.	1
		Significance	p < .01			Significance	not sig

4.6.2 Predictive Power and Adequacy of Model

The collected data were analyzed using the multinomial logistic regression technique in the Sawtooth Software Lighthouse Studio program (Sawtooth Software, Inc., 2021) and the model was estimated.

When the predictive power and adequacy of the model are examined, the log-likelihood for this model was found as -1101.10639 where the log-likelihood for the null model is -1280.93599.

Since the chi-square formula is

$$\chi^2 = 2(loglikelihood_{estimated} - loglikelihood_{null})$$

the difference between this model and the null model was found as 179.82960. Therefore, twice the value of difference gives the chi-square value which was found as $\chi^2 = 359.65920$. The degree of freedom in the model is found with the difference between the number of levels used and number of attributes used. There are 20 levels for 8 features in the study. In this case, the degrees of freedom are found as $d = 20 - 8 = 12$.

"H_0 : There is no significant affection between the choices of the students and the attributes and attribute levels used."

"H_1 : There is a significant affection between the choices of the students and the attributes and attribute levels used."

When the hypotheses established above are examined at 99% and 95% significance level; the chi-square table values for $d = 12$ are found as $\chi^2_{0.99} = 26.217$ and $\chi^2_{0.95} = 21.026$.

Since $\chi^2 = 359.65920 > \chi^2_{0.99} = 26.217$ and $\chi^2 = 359.65920 > \chi^2_{0.95} = 21.026$, the H_0 hypothesis is rejected. This shows that the student' choices are significantly affected by the combination of attributes and their levels.

4.6.3 Part Worth Utilities of Attribute Levels

The part worth utilities of the attribute levels as a result of Hierarchical Bayesian Estimation are as in Table 8. In the table, part worth utilities are shown as normalized utilities. That is, utility values with zero-centered difference were created for the attributes. So, it appears that the sum of the utilities of the levels for each attribute gives zero. This is because the data coding for analysis is done with effects-coding and the last level of each attribute is omitted. Thus, the utility of the last level is formed as the negative of the sum of the utilities of the other levels. After these explanations, the results for each attribute are interpreted.

For the first attribute, the theoretical lecture, three levels were used: face-to-face, online, both face-to-face and online. At the end of the estimation, it was found that the students preferred the face-to-face lecture the most (part worth utility 28.93). Then, it is seen that they prefer to access the resources online in addition to the face-to-face course (part worth utility 17.57). If students have online education, their utilities will decrease (part worth utility -46.50).

The problem-solving session is a three-level attribute. These attributes are leveled as no question-solving session, having a session in which the lecturer solves questions in the classroom, and giving additional assignments to the lecturer's question-solving session. According to the results, students mostly prefer the lecturer makes a question-solving session (part worth utility 34.69). Secondly, while they prefer the lecturer to be given homework in addition to the question solution session (part worth utility 26.03), they think that their benefits will decrease if there is no question solution session (part worth utility -60.32).

In the determination of the term project groups, the preferences of the students are that the lecturer determines the groups randomly and the students determine the groups themselves. Students prefer to determine for themselves that the part worth utility is 50.04. The other option, the lecturer’s determination, has part worth utility of -50.04, as it is a zero-centered differential estimation, as mentioned before. This means that it reduces the utility.

While determining the number of people in the groups, alternatives with groups of 2, 4 and 6 people were directed to the students. While the level most preferred by the students is 28.00, the level of 4 people with part worth utility, it is seen that the other two levels reduce the utility (part worth utilities -7.43 and -20.57 respectively)

When analyzing whether students prefer to have a term project presentation, it is seen that students prefer not to make a presentation (part worth utility 32.35). Since this attribute is bi-level, the other level it is negative of the part worth utility of the other level.

When we look at the preferences of the students about whether the term project will be submitted in one or two times, it is seen that the students prefer to make a single submission. The part worth utility of this level was determined as 10.53. However, as mentioned before, there is no significant difference between these levels. This can be interpreted by the low value of the part worth utility.

For the examination attribute, among the options with only quiz, only final exam, and both quiz and final exam, students prefer only quiz with a part worth utility value of 82.74. The other two levels reduce students' utility. However, the most obvious loss of utility occurs in the case of both the quiz and the final exam will be take place.

Another attribute where there is no significant difference between the levels is the type of quiz attribute, which is used to determine how the quiz will take place. Here, students prefer the quiz to be done in the classroom with a part worth utility value of 2.60.

The utility function obtained for course design in x_{ij}, where i the is attribute and j is the level, is as follows.

$$Y = 28.93x_{11} - 46.50x_{12} + 17.57x_{13} - 60.72x_{21} + 34.69x_{22} + 26.03x_{23} - 50.04x_{31} + 50.04x_{32} - 7.43x_{41} + 28.00x_{42} - 20.57x_{43} + 32.25x_{51} - 32.35x_{52} + 10.53x_{61} - 10.53x_{62} + 82.74x_{71} - 1.33x_{72} - 81.40x_{73} + 2.60x_{81} - 2.60x_{82}$$

Table 8: Part Worth Utilities

Attribute	Attribute Levels	Utility	Std Deviation	Lower 95% CI	Upper 95% CI
Theoretical Lecture	Face to face learning	**28.93**	36	20.94	36.92
	Online learning	-46.5	32.73	-53.76	-39.24
	Both face to face and online learning	17.57	26.97	11.59	23.56
Problem-Solving Session	No problem-solving session	-60.72	35.95	-68.7	-52.74
	Problem solving in theoretical lecture	**34.69**	31.54	27.69	41.69
	Problem solving in theoretical lecture and additional practices	26.03	29.54	19.47	32.58
Term Project Groups	Lecturer assigns randomly	-50.04	54.34	-62.09	-37.98
	Students determine the groups	**50.04**	54.34	37.98	62.09
Number of People	Group of 2 students	-7.43	51.66	-18.9	4.03
	Group of 4 students	**28**	39.5	19.24	36.77
	Group of 6 students	-20.57	38.21	-29.05	-12.09
Term Project Presentation	No	**32.35**	31.81	25.29	39.41
	Yes	-32.35	31.81	-39.41	-25.29
Term Project Submission	1-time submission	**10.53**	31.53	3.53	17.53
	2-times submission	-10.53	31.53	-17.53	-3.53
Examination	Quiz only	**82.74**	78.26	65.37	100.1
	Final exam only	-1.33	53.09	-13.12	10.45
	Both Quiz and Final Exam	-81.4	60.88	-94.92	-67.89
Type of Quiz	In-class	**2.6**	25.28	-3.01	8.22
	Online	-2.6	25.28	-8.22	3.01
NONE	None	139.72	175.49	100.77	178.66

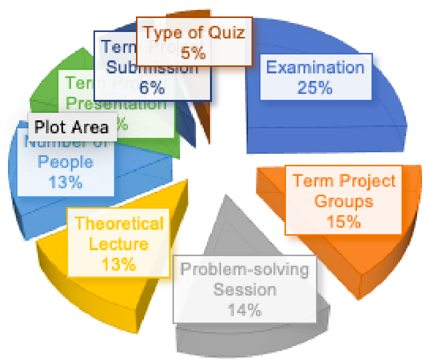
4.6.4 Average Importance of Attributes

The average importance of the attributes were determined from the experimental data analyzed using the Hierarchical Bayesian Estimation method. Results can be seen in Table 9. According to the results, the three most important attribute of the students are examination, term project groups and problem-solving session. In other words, which exams will be held, how the term project groups will be determined, and if there is a question-solving session, how it will take place are students' three important attributes. The order of importance can also be seen the pie chart (See: Figure 17).

Table 9: Average Importance of Attributes

Attribute	Importance	Std Deviation	Upper 95% CI	Upper 95% CI
Examination	24.70	11.86	22.07	27.34
Term Project Groups	15.41	10.13	13.16	17.65
Problem-solving Session	14.42	6.15	13.06	15.79
Theoretical Lecture	12.62	4.82	11.55	13.69
Number of People	12.54	5.94	11.22	13.86
Term Project Presentation	9.10	6.76	7.60	10.60
Term Project Submission	6.39	5.27	5.22	7.56
Type of Quiz	4.82	4.11	3.90	5.73

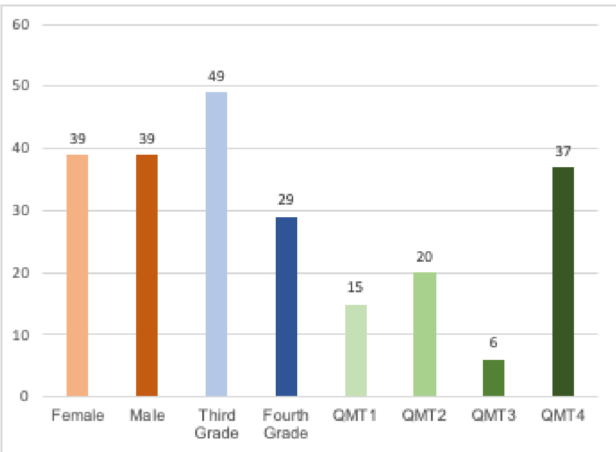
Figure 17: Average Importance of Attributes



4.6.5 Analyzing the Part Worth Utilities According to the Demographic Characteristics of the Students

As mentioned before, including demographic questions in the DCEs gives the researcher an idea about whether the choices have changed for different groups. If the researcher will target an even narrower group within the determined domain, he can decide the product and service in line with the choices of that group. Target group of the study is the students who are taking the course in that term. Demographic characteristics of the study, in which 78 students participated in total, are as in Figure 18. When we look at the genders, 39 students are female, and 39 students are male. 49 students are from third grade and 29 students are from fourth grade. When we look at the Quantitative Methods (QMT) elective course choices, 15 students have taken the QMT elective before but will no longer take it (QMT1), 20 students have taken the QMT elective before and will continue to take it (QMT2), 6 students have not taken the QMT elective before but plan to take it (QMT3), and 37 students declared that they did not take the elective course and will not plan to take it either (QMT4). These choices especially help to have an idea about interest to the course. Because the Business Forecasting course is also a QMT course, and it is thought that the disposition will change the choices.

Figure 18: Demographic Characteristics



Now, part worth utilities according to the demographic characteristics will be mentioned.

When the utility values of the levels of the attributes according to the gender of the students are examined, for almost all attributes and their levels, it is seen that the order of preference remains the same even if the values change. The only difference is that women prefer online quizzes for the type of quiz attribute. Therefore, we can conclude that the gender variable does not change student preferences. Likewise, when the part worth utilities of the attributes according to the grades of the students are examined, it is concluded that there is no change in the preferences of the third and fourth grade students. For this reason, the table is not used to show the part worth utilities for these two demographic characteristics.

Table 10 shows the changes in students' preferences according to whether they take Quantitative Methods (QMT) elective courses or not. Different responses are shown in bold. Course choices, which can also be interpreted as students' interest in QMT, emerge as a difference in their choices regarding the design of the course. In this classification, where most of the students' choices for the attribute are similar, the students who have taken the course before and will not take it in the future and the students who will not take the course before and will take the course in the future (column 1 and 3) prefer online quizzes. In addition, students who will take the course before and will continue to take the course prefer face-to-face teaching and support with online resources, and additional practices along with a problem-solving session.

Table 10: Part Worth Utilities of Attributes According to Students' QMT Elective Preferences

Attribute	Attribute Levels	1*	2*	3*	4*
Theoretical Lecture	Face to face learning	27.82	18.38	34.24	34.22
	Online learning	-49.7	-45.2	-44.07	-46.3
	Both face to face and online learning	21.88	**26.82**	9.83	12.08
Term Project Submission	1-time submission	23.03	2.32	-2.13	11.95
	2-times submission	-23.03	-2.32	**2.13**	-11.95
Type of Quiz	In-class	-2.87	10.51	-6.72	2.07
	Online	**2.87**	-10.51	**6.72**	-2.07
Examination	Quiz only	94.04	61.56	87.37	88.85
	Final exam only	-0.73	-5.87	-16.98	3.41
	Both Quiz and Final Exam	-93.31	-55.69	-70.39	-92.26
Term Project Presentation	No	24.5	42.04	41.17	28.86
	Yes	-24.5	-42.04	-41.17	-28.86
Number of People	Group of 2 students	-11.24	-2.6	-24.51	-5.73
	Group of 4 students	31.25	30.48	36.63	23.95
	Group of 6 students	-20.01	-27.88	-12.12	-18.22
Problem-Solving Session	No problem solving session	-60.02	-50.85	-54.17	-67.4
	Problem solving in theoretical lecture	41.81	14.72	38.96	41.91
	Problem solving in theoretical lecture and additional practices	18.21	**36.13**	15.2	25.49
Term Project Groups	Lecturer assings randomly	-45.29	-43.17	-39.21	-57.43
	Students determine the groups	45.29	43.17	39.21	57.43

1: Those who have previously taken QMT elective and will not continue to receive it

2: Those who have previously taken QMT elective and will continue to receive it

3: Those who did not take QMT elective before and plan to buy it in the future

4: Those who did not take QMT elective before and plan not to take it in the future

4.7 CREATING COURSE ALTERNATIVES

As a result of the first experiment, the relative order of importance of the alternatives and the levels that maximize utility within the alternatives were found. At this stage, course alternatives will be created for the next experiment according to the data obtained. The process of creating course alternatives was carried out by the researcher and the lecturer working together. While designing, none of the alternatives are alienated from reality, that is, one day it can be used as a way of teaching the course.

For the next experiment, four different course designs were created and are as in Table 11. Two of the design alternatives were determined as course alternatives that maximize (See: Alternative 2) and minimize (See: Alternative 3) the utility, as a result of data analysis. It was used as the state of the course before the new design is made (See: Alternative 1). The last course alternative has been determined as the situation that the course has to take as a result of the transition from face-to-face education to online education during the Covid-19 pandemic (See: Alternative 4).

The identified alternatives were presented to the students on separate cards. In order to be visually simple and understandable, the attributes used in the previous experiment were grouped and each determined level was explained next to the relevant attribute/attribute group.

The utility values for the 4 alternatives are as follows.

$$Y_{A_1} = 28.93 + 26.03 + 82.74 + 2.60 - 50.04 - 10.53 - 32.35 - 7.43 = 39.95$$

$$Y_{A_2} = 17.57 + 34.69 + 82.74 + 2.60 + 50.04 + 28.00 + 32.35 + 10.53 = 258.52$$

$$Y_{A_3} = -46.50 - 60.72 - 81.40 - 2.60 - 50.04 - 10.53 - 32.35 - 20.57$$
$$= -562.11$$

$$Y_{A_4} = -46.50 + 26.03 - 81.40 + 50.04 + 28.00 + 32.35 - 2.60 + 10.53 = 16.45$$

As can be seen, the version of the course before this study (Alternative 1) already has a positive utility value of 39.95. However, it is possible to increase this utility approximately 6.5 times if a course design is made by considering the preferences of the students (See: Alternative 2). What is more interesting is that the third course alternative, which is made from levels that are not preferred by the students, seriously reduces the utility of the students. Finally, the way the course is handled during the pandemic (See: Alternative 4), although it produces a positive utility value, has a utility value of approximately 2.5 times lower compared to the first version of the course. Students' perceptions and feelings will be determined for these alternatives produced in the following parts of the study.

Table 11: Course Alternatives Created

	Alternative 1	**Alternative 2**	**Alternative 3**	**Alternative 4**
Theoretical lecture	x_{11}: Face to face learning	x_{13}: Both face to face and online learning	x_{12}: Online learning	x_{12}: Online learning
Problem solving session	x_{23}: Lecturer solves problems in class and gives at-home practices	x_{22}: Lecturer solves problem in class	x_{21}: No problem-solving session	x_{23}: Lecturer solves problems in class and gives at-home practices
Examination	Midterm x_{41}: In-class quiz x_{31}: No final	Midterm x_{41}: In-class quiz x_{31}: No final	Midterm x_{42}: Online quiz x_{32}: Final	Midterm x_{42}: Quiz x_{32}: Final
Term project	x_{51}: Lecturer forms the groups x_{61}: Group of 2 people x_{82}: Term project presentation x_{72}: 2-times submission	x_{52}: Students form the groups x_{62}: Group of 4 people x_{81}: No term project presentation x_{72}: 2-time submission	x_{51}: Lecturer forms the groups x_{61}: Group of 2 people x_{82}: Term project presentation x_{72}: 2-time submission	x_{52}: Students form the groups x_{62}: Group of 4 people x_{81}: No term project presentation x_{71}: 1-time submission
Utility Obtained	**39.95**	**258.52**	**-562.11**	**16.45**

4.8 CONDUCTING KANSEI ENGINEERING STUDY

Experiment was designed in Sawtooth Software Lighthouse Studio v9.11.0 by using SD scale question in the general survey question menu (Sawtooth Software, Inc., 2021). The products created as a result of DCE were introduced with the product cards and product introduction texts (See: Figure 19).

Figure 19: Presentation of Course Alternatives on KEE

The first alternative of the Business Forecasting Course has the following features:

Obtaining theoretical knowledge: Face to face learning in the classroom
Problem solving opportunities of the theoretical lecture: In addition to problem solving session in the class, at-home practices will be also given.
Type of Examination: Midterm exam is a must. Instead of final exam a quiz will be held in the class
Attributes of Term Project: For the project, students will form their four-member groups on their own. The term project will be delivered in two parts and no presentation will be made for the project.

Business Forecasting Course Alternative 1

Obtaining Theoretical Knowledge:	Face to Face Learning
Problem Solving Opportunities	Lecturer solves problems in class and gives at-home practices
Type of Examination	Midterm
	In-class Quiz
	No Final
Term Project Features	Lecturer forms the groups
	Group of 2 people
	Term project presentation
	2-time submission of project

Please select appropriate option by sliding the circle between two extreme attributes below.

The words used in the study will be displayed as word pairs and evaluated with a SD scale. As mentioned before, 5-point semantic differential scale was preferred for ease of use. While creating KW pairs, it was preferred to use denials instead of antonyms as much as possible. Thus, 10 KW pairs were placed on 5-point SD scale and students were asked to select the point on the scale for each word describing the above course alternative on the scale.

Although the experiment was conducted in English, word pairs were given in both English and Turkish (See: APPENDIX III). Thus, the problems that may occur due to not knowing the word or not being able to make sense of it were tried to be eliminated.

4.9 DATA ANALYSIS FOR KANSEI ENGINEERING EXPERIMENT

40 students from Dokuz Eylül University Faculty of Business participated in the online Kansei Engineering Experiment. 21 of the students are female, and 19 is male. 1 of the students is from 3rd grade, 35 of them are from 4th grade, and 4 of them were graduated. The reason why the demographic characteristics of the participants of the two experiments differed is that the second experiment was carried out a few months later due to the Pandemic. During the second experiment, the 3rd year students became the 4th year and 4th year students were graduated.

While performing the data analysis, the reliability of SD scale was measured first. Then, with the Principal Component Analysis, dimension reduction was made for grouping the words and the word structure was revealed. Finally, the relationship between course attributes and Kansei words was estimated using the Partial Least Squares Regression method. Below are the details of all these analyzes.

4.9.1 Reliability Analysis

The data collected before the reliability analysis were arranged and the rows with missing data were cleaned. Then, scale reliability was evaluated with Cronbach Alpha for 10 KW pairs. Alpha value was found to be 0.855. For a reliable scale, the value is expected to be 0.7 and above. This shows that the scale is highly reliable. However, as shown in bold in Table 12, removing the Decentralized-Centralized KW pair from the analysis significantly increases the scale reliability.

Table 12: Cronbach Alpha values when KW is deleted

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Abstract-Concrete	,633	,835
Centralized- Decentralized	**-,115**	**,891**
Individualistic-Collaborative	,443	,851
Not Satisfactory-Satisfactory	,703	,828
Basic-Advanced	,424	,852
Not Educational-Instructional	,719	,827
Noneffective-Effective	,774	,821
Noninteractive-Interactive	,681	,831
Disorganized- Organized	,729	,827
Nonanalytical-Analytical	,638	,835

4.9.2 Revealing the Kansei Word Structure

Revealing the KW structure is done by Principal Component Analysis (PCA). Before doing PCA, the suitability of the variables, that is, whether the words are correlated to each other, was examined. The correlation matrix of the data set was created using the right tails of the word pairs. As seen in Table 13, it was concluded that most of the words were related at 0.01 and 0.05 significance levels. It was decided that the word 'decentralization', which is not related to any other Kansei words, should not be included in the PCA.

Table 13: Correlation Matrix of Kansei Words

		concrete	decentralized	collaborative	satisfactory	advanced	instructional	effective	interactive	organized	analytical
concrete	Pearson Correlation	1									
	Sig. (2-tailed)										
	N	40									
decentralized	Pearson Correlation	-0.108	1								
	Sig. (2-tailed)	0.506									
	N	40	40								
collaborative	Pearson Correlation	.436**	-0.277	1							
	Sig. (2-tailed)	0.005	0.083								
	N	40	40	40							
satisfactory	Pearson Correlation	.698**	-0.225	.475**	1						
	Sig. (2-tailed)	<.001	0.163	0.002							
	N	40	40	40	40						
advanced	Pearson Correlation	0.073	-0.067	0.262	0.283	1					
	Sig. (2-tailed)	0.653	0.682	0.102	0.076						
	N	40	40	40	40	40					
instructional	Pearson Correlation	.589**	0	0.288	.675**	0.096	1				
	Sig. (2-tailed)	<.001	1	0.072	<.001	0.557					
	N	40	40	40	40	40	40				
effective	Pearson Correlation	.611**	0.033	0.31	.731**	0.084	.861**	1			
	Sig. (2-tailed)	<.001	0.838	0.052	<.001	0.608	<.001				
	N	40	40	40	40	40	40	40			
interactive	Pearson Correlation	.511**	-0.269	.659**	.650**	0.305	.573**	.627**	1		
	Sig. (2-tailed)	<.001	0.093	<.001	<.001	0.056	<.001	<.001			
	N	40	40	40	40	40	40	40	40		
organized	Pearson Correlation	.611**	-0.17	0.312	.791**	.372*	.591**	.656**	.601**	1	
	Sig. (2-tailed)	<.001	0.293	0.05	<.001	0.018	<.001	<.001	<.001		
	N	40	40	40	40	40	40	40	40	40	
analytical	Pearson Correlation	.480**	-0.228	0.093	.575**	.395*	.693**	.619**	.445**	.728**	1
	Sig. (2-tailed)	0.002	0.158	0.567	<.001	0.012	<.001	<.001	0.004	<.001	
	N	40	40	40	40	40	40	40	40	40	40
**. Correlation is significant at the 0.01 level (2-tailed).											
*. Correlation is significant at the 0.05 level (2-tailed).											

Bartlett Test of Sphericity and Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy are used to determine the suitability of the data structure for PCA (See: Table 14). Since the value of 0.815 for the KMO criterion is between 0.80 and 0.89, it is concluded that the sample size was sufficient for PCA. In addition, according to the Bartlett Test of Sphericity ($p < 0.001$), the correlation matrix is not orthogonal, in other words, the data set contains sufficient dependency. In this case, it is concluded that the data set is suitable for PCA.

Table 14: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.815
Bartlett's Test of Sphericity	Approx. Chi-Square	244.451
	df	36
	Sig.	<.001

The communalities obtained as a result of Principal Component Analysis are given in Table 15. These values represent the percentage of variance of each variable that can be explained by the components. Satisfactory results were obtained in terms of the success of the analysis, as the percentage of variance explanation for almost all variables was over 70%.

Table 15: Communalities

KW	Initial	Extraction
concrete	1.000	.669
collaborative	1.000	.912
satisfactory	1.000	.798
advanced	1.000	.931
instructional	1.000	.819
effective	1.000	.844
interactive	1.000	.778
organized	1.000	.790
analytical	1.000	.863

Table 16 shows the variance explanation rates achieved by PCA. The Kaiser rule was applied while determining the number of components. According to the rule, factors with an eigenvalue of at least 1 should be taken while determining the number of components (Kaiser, 1960). According to the table, the eigenvalues of the first three components are greater than 1. In this case, our data set containing 10 Kansei words as a result of PCA has been reduced to three components and these components explain 82.26% of the total variance. The variance explanation rates of the components are 57,288%, 13,059% and 11,916%, respectively.

While deciding on the number of components, the scree plot drawn according to the percentage of variance explained and eigenvalues are used. According to the scree plot for this study (See: Figure 20), it is seen that the components after the first three components do not contribute significantly to the explanation of the variance. One can also say that the size can be reduced to three with the scree plot.

Figure 20: Scree Plot

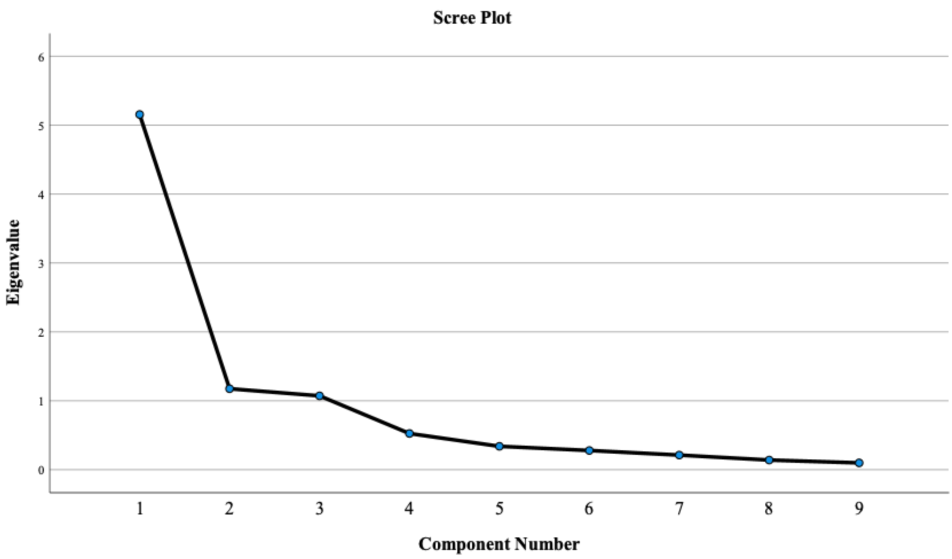


Table 16: Total Variance Explained

Component	Initial Eigenvalues		Extraction Sums of Squared Loadings		Rotation Sums of Squared Loadings[a]
	Total	Cumulative %	Total	Cumulative %	Total
1	5.156	57.288	5.156	57.288	4.87
2	1.175	70.347	1.175	70.347	2.29
3	1.072	82.263	1.072	82.263	1.563
4	0.526	88.105			
5	0.34	91.878			
6	0.279	94.978			
7	0.212	97.339			
8	0.14	98.897			
9	0.099	100			

Table 17 shows the pattern matrix after oblique rotation for the three components obtained by Principal Component Analysis. In the table, components with words according to their loadings are shown in bold. According to their loadings, the first component contains the word pairs not educational-instructional, non-effective-effective, not analytical-analytical, disorganized-organized, not satisfactory-satisfactory and abstract-concrete. The words grouped in the first component can be defined under the heading '**structure'**. In this component, the words will help to have information about the structure of the course. By using these words, students can express their feelings about the structure of the course.

The second component contains individualistic-collaborative and not interactive-interactive word pairs. The second component containing these words can be identified with the title '**participation'**. Here, what is meant by the level of participation is the extent to which the students are present in the course. In terms of workload, students can have a collaborative course by working as a group for term project or they can be individual while their performances are measured. Likewise, the course can be completed only with lecturer's teaching, or it can be realized in an interactive way with active participation of the students.

The third component contains only basic-advanced word pairs. This component can be titled as '**difficulty'** and it can define whether the course is taught at basic, intermediate, or advanced level.

Table 17: Pattern Matrix

KW	Component		
	1	2	3
concrete	**.699**	.280	-.170
collaborative	-.007	**.945**	.097
satisfactory	**.744**	.268	.092
advanced	-.047	.140	**.956**
instructional	**.936**	-.039	-.141
effective	**.926**	.038	-.165
interactive	.445	**.590**	.143
organized	**.765**	.033	.298
analytical	**.842**	-.317	.348

Table 18, that shows which words are included in which components, is below.

Table 18: Component Table

Component	Left side	Right side
structure	abstract	concrete
	not satisfactory	satisfactory
	not educational	educational
	non effective	effective
	not organized	organized
	non analytical	analytical
participation	individualistic	collaborative
	not interactive	interactive
difficulty	basic	advanced

4.9.3 Relationship Formation

In KEE, product alternatives created were evaluated using Kansei words. By doing PCA, 10 KW pairs were first reduced to a three-dimensional structure. In this step, the relationship between the determined components and the course characteristics will be established. Partial Least Squares (PLS) Regression will be used to establish this relationship.

The explained variance proportions of the components are as in the Table 19. In Kansei engineering studies, the recommended R-square value is 0.8 and above. It can be seen that this value is approximately 0.9 for all three components. Therefore, course attributes are sufficient to explain Kansei words.

Table 19: Explained Variance Proportion for Component

Component	X variance	Y variance	Adjusted R-square
PC1 (structure)	0.332	0.931	0.897
PC2 (participation)	0.306	0.963	0.944
PC3 (difficulty)	0.298	0.979	0.969

The relationship of a principal components with course attributes is as in the functions below. When the relationship between Kansei words and course attributes is analyzed, suppose PC1, PC2 and PC3, in which Kansei words are grouped, be the dependent variable and x_{ij} where the $i = 1,2, \ldots, n$ is the course attribute and $j = 1,2, \ldots, m$ is the attribute levels are the independent (explanatory) variable. For the presence of the explanatory variable, it is assigned 1 and for the absence of the explanatory variable, it is assigned 0. This kind of variable is called dummy variable. So,), $x_{ij} = 1$ indicates that the jth level of ith attribute is included in the alternative, and $x_{ij} = 0$ indicates that it is not included. In short, for modelling the relationship between the principal component and course attributes, the dummy variable is used.

$$\begin{aligned} PC1(x) = 3.375 &+ 0.094x_{11} - 0.097x_{12} + 0.035x_{13} - 0.168x_{21} + 0.035x_{22} + 0.100x_{23} \\ &+ 0.097x_{31} - 0.097x_{32} + 0.094x_{41} - 0.094x_{42} - 0.056x_{51} + 0.056x_{52} \\ &- 0.056x_{61} + 0.056x_{62} - 0.039x_{71} + 0.039x_{72} + 0.056x_{81} - 0.056x_{82} \end{aligned}$$

$$\begin{aligned} PC2(x) = 3.503 &+ 0.125x_{11} - 0.135x_{12} + 0.054x_{13} - 0.200x_{21} + 0.054x_{22} + 0.110x_{23} \\ &+ 0.135x_{31} - 0.135x_{32} + 0.125x_{41} - 0.125x_{42} - 0.056x_{51} + 0.056x_{52} \\ &- 0.056x_{61} + 0.056x_{62} + 0.021x_{71} - 0.021x_{72} + 0.056x_{81} - 0.056x_{82} \end{aligned}$$

$$\begin{aligned} PC3(x) = 3.443 &+ 0.083x_{11} - 0.091x_{12} + 0.039x_{13} - 0.118x_{21} + 0.039x_{22} + 0.059x_{23} \\ &+ 0.091x_{31} - 0.091x_{32} + 0.083x_{41} - 0.083x_{42} - 0.026x_{51} + 0.026x_{52} \\ &- 0.026x_{61} + 0.026x_{62} - 0.004x_{71} + 0.004x_{72} + 0.026x_{81} - 0.026x_{82} \end{aligned}$$

Accordingly, the degrees of explaining the components with the alternative that maximizes students' utility were found as 3.711, 4.018 and 3.777, respectively. In the study using the 5-point SD scale, the value of 3.4 was determined as the reference value. Thus, the values show that course attributes have high success in explaining the components.

Finally, since fewer number of KW used in the demonstration, the dimension of the relationship between all Kansei words and course attributes was also examined. The R-square value was found to be 0.927 in PLS for all words. According to the PLS analysis, the output table showing the parameter values of the relationship between Kansei words and product attributes is given in Table 20 and the formulas above were used and the results for the alternatives created were found as in the Table 21.

Again, according to the reference value of 3.4, the Kansei words explanation rates of the attributes are shown in the bottom line of the table.

The results for Alternative 1 and Alternative 2 are very similar. While the rate of explaining Kansei words of Alternative 1, which shows the way the course was taught before the design, was 77.8%, the rate of explaining Kansei words of the Alternative 2, which maximizes the utility of the students after DCE, was found to be 66.7%. While the compulsory form taken by the course due to the pandemic has a rate of 22.2%, the alternative that minimizes student benefit cannot be explain any Kansei word.

Table 20: Parameters

Product Attributes	k_{10}	k_9	k_8	k_7	k_6	k_5	k_4	k_3	k_1
(Constant)	3.528	3.561	3.468	3.342	3.485	3.443	3.177	3.523	3.266
x_{11}	0.103	0.099	0.107	0.117	0.14	0.083	0.067	0.11	0.084
x_{12}	-0.094	-0.085	-0.102	-0.109	-0.145	-0.09	-0.093	-0.124	-0.1
x_{13}	0.022	0.014	0.029	0.028	0.054	0.039	0.058	0.055	0.051
x_{21}	-0.171	-0.162	-0.167	-0.181	-0.207	-0.12	-0.151	-0.193	-0.18
x_{22}	0.022	0.014	0.029	0.028	0.054	0.039	0.058	0.055	0.051
x_{23}	0.111	0.111	0.104	0.114	0.115	0.059	0.069	0.103	0.095
x_{31}	0.094	0.085	0.102	0.109	0.145	0.091	0.093	0.124	0.101
x_{32}	-0.094	-0.085	-0.102	-0.109	-0.145	-0.09	-0.093	-0.124	-0.1
x_{41}	0.103	0.099	0.107	0.117	0.14	0.083	0.067	0.11	0.084
x_{42}	-0.103	-0.099	-0.107	-0.117	-0.14	-0.08	-0.067	-0.11	-0.08
x_{51}	-0.05	-0.047	-0.045	-0.047	-0.05	-0.03	-0.063	-0.062	-0.07
x_{52}	0.05	0.047	0.045	0.047	0.05	0.026	0.063	0.062	0.07
x_{61}	-0.05	-0.047	-0.045	-0.047	-0.05	-0.03	-0.063	-0.062	-0.07
x_{62}	0.05	0.047	0.045	0.047	0.05	0.026	0.063	0.062	0.07
x_{71}	0.045	0.048	0.031	0.035	0.013	-0	0.026	0.028	0.042
x_{72}	-0.045	-0.048	-0.031	-0.035	-0.013	0.004	-0.026	-0.028	-0.04
x_{81}	0.05	0.047	0.045	0.047	0.05	0.026	0.063	0.062	0.07
x_{82}	-0.05	-0.047	-0.045	-0.047	-0.05	-0.03	-0.063	-0.062	-0.07

Table 21: Relationship Between Product Attributes and Kansei Words

Kansei words	**Alternative 1**	**Alternative 2**	**Alternative 3**	**Alternative 4**
concrete	3.294	3.343	2.551	3.327
satisfactory	3.646	3.619	2.758	3.482
instructional	3.191	3.293	2.558	3.208
effective	3.602	3.533	2.986	3.311
organized	3.722	3.585	2.685	3.333
analytical	3.506	3.355	2.65	3.297
collaborative	3.615	3.500	2.824	3.427
interactive	3.667	3.527	2.941	3.592
advanced	3.641	3.518	2.871	3.543
percentage	**77.8%**	**66.7%**	**0**	**22.2%**

CONCLUSION

Today, customers have become aware of what they want and therefore careful in their choices. With the development of technology, they can easily access any information they want. Companies are also in a tough competition where they try to do their best to satisfy the customers. In today's highly competitive market, customer orientation is at the forefront of the policies adopted by companies to be successful. Companies that put the customer in their focus should shape all their organizational structures in this way, and customer-oriented companies should observe, anticipate and act according to the wishes and needs of the customers. Moving from this fact, consumer behavior studies have also gained momentum both in literature and practice.

The Discrete Choice Experiment is a method that includes experimental design and analysis. In this method, hypothetical alternatives created from product attributes are presented to customers and they are asked to choose the alternative they prefer. Since it is assumed that people will choose the alternative that maximizes their utility, at the end of the experiment, it is aimed to determine the product alternative that maximizes the utility of the people, to reveal the part worth utilities of each attribute, and rank the product attributes in importance.

Kansei Engineering, on the other hand, is an engineering method that reveals the perceptions and feelings of consumers and transforms it into design elements. With Kansei Engineering, it is aimed to design the product that affects them by eliciting the images in the minds during product choice. This method, which makes customer-oriented design by relating the attributes of the product and the perception and feelings of the customers, is used in the design of especially large products such as houses and cars by taking advantage of the developing technology.

The aim of this study is to propose a choice model that reveals both product attributes and perceptions and emotions about that product by using these two methods together. This model will be able to model the choice process of all products and services and be used in the design process of these product and services. Also, the fact that the product is existed in the market or not existed does not change the applicability of the model.

Since customers are at the center of this model by including them to all processes of all experiments to be carried out, the model is described as customer oriented. Being customer-oriented ultimately enables product design to be tailored to the customers' needs and feelings.

In the proposed model, two consecutive experiments are conducted. But, before the experiments, it is determined which product will be used and which group it will target. Then, product attributes and Kansei words are revealed by spanning the product space and semantic space. In the first experiment, hypothetical alternatives created using product attributes are presented to the target people and their choices are collected. Then the results are analyzed with discrete choice models. As a result of the analysis, the researcher creates the product in line with goal of the study and the second experiment is performed. In the second experiment, the words coming from the identification of Kansei words stage are used for evaluation of product alternatives created. In short, the product alternatives are evaluated with the Kansei words on the SD scale. As a result, the relationship between words and attributes was revealed using multivariate data analysis methods.

In this study, in order to test the applicability of the model, the model was demonstrated on a course design. First of all, focus group study was carried out for product space and semantic space spanning. At the end of this study, the structure, components, and problems of the course were revealed, and a 60-word KW list is prepared. For the first experiment, the product structure, components, and problems were evaluated. Then, the lecturer and the researcher worked together to decide on the course attributes. In total, eight course attributes are introduced under three groups. The first group "lecture" consists of two attributes. How the theoretical course will be taught and how the problem-solving session will take place are the attributes in this group. In the second group "examination", there are attributes about which exams will take place and how the quiz will be handled. Finally, the third group "term project", have attributes such as how many people the groups will consist of, who will determine the groups, whether there will be a term project presentation and how many times the term project will be delivered.

The experiment was designed using Sawtooth Software Lighthouse Studio with the specified attribute and levels. In total, 14 choice sets, two of which are fixed and twelve of which are random, are presented to the students. Each choice set includes three course alternatives and an option to choose none of them. After the experiment, the version in which it was taught in the previous years, the versions that maximized and minimized the student utilities according to the results of the experiment, and the version in which the lecture was taught during the Covid-19 pandemic were turned into course alternatives. The predicted utility scores for each alternative are 39.95, 258.52, -562.11 and 16.45 respectively. Therefore, it was also estimated that the alternative maximizes the utility of the students will yield 6.5 times more utility than the lecture that was taught in previous years. The way the course is taught during the pandemic also provides 0.41 times less utility than the lecture taught in previous years. These scores are important as they will be used to reveal the relationship between utilities and student's success.

For the second experiment, the 60-word Kansei list was first converted into 10-word pairs using the affinity diagram. It was then placed on the 5-point SD scale. Students were asked to evaluate each alternative created with these word pairs. After the evaluations, the experiment was completed, and data was collected. The collected data was first analyzed with principal component analysis and the words were grouped. It has been revealed that 10 words can be grouped into three components according to PCA. These components are named as structure, participation, and difficulty, respectively. Then, the relationship between course attributes and words was revealed by partial least squares regression. Kansei words with a scale average of 3.4 and above were used and the percentage of explanations of the alternatives was found. Here, the first alternative was explained by 77.8% of the Kansei words, the second alternative by 66.7%, and the fourth alternative by 22.2%. Similar results were obtained for Alternative 1 and Alternative 2. Most of the words explain Alternative 1 because students are already familiar with this course concept. With the implementation of the second alternative, it is expected that the utility of the students will increase, and the course alternative will be explained with more words.

The study was carried out with certain limitations. The first of these limitations is the Covid-19 pandemic. At the beginning of the study, it was planned that the lecture designed by using the model to be used as a lecture for the remainder of the term. However, while the first experiment was just being completed, the Covid-19 pandemic started, and the education began to be carried out completely online. Thus, the lecture took on a completely different form than the one that appeared. For this reason, at the end of the design, it could not be tested whether there is a relationship with the estimated utility increase in the course outcomes.

The remaining limitations are time related. Demonstration had to be done quickly, as the design would be used for the remainder of the term. For this reason, a pre-experiment study was not carried out for both experiments. In the first experiment, the effectiveness of the experimental design could be measured by performing a preliminary experiment. Since such a measurement could not be performed, it was later realized that the prohibitions reduced the efficiency.

Prohibitions used are also one of the limitations. Since it was necessary to act quickly, the prohibitions were arranged so that the conflicting or incompatible attribute levels were not shown to the students in the experiment. However, it was possible to perform the experiment without the need for prohibitions by better specifying the attribute levels.

Finally, before the second experiment, if factor analysis was preferred instead of affinity diagram, it would have been possible to choose more proper words in the experiment. However, because the pre-experiment study with a 60-word list would take a lot of time and it was difficult to find participants for this long study, words were determined with the affinity diagram. In the experiment from ten words were used, one word was not associated with any other words. As a result, it could be more appropriate to conduct a preliminary experiment and analyze the study with quantitative methods.

The proposed model has the goal of predicting the choice process of all products and services and designing these products in accordance with this prediction. In this context, measuring the effectiveness of the model by applying it to different products and services is still requiring further studies. In addition, measuring the effectiveness of the new course design by using the results of the demonstration and determining the relationship between the increase in utility and student success are among the studies that are planned to be done in the future.

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APPENDICES

APPENDIX I: Focus Group Study Question Form

I. Please write first five emotions that come to your mind about Business Forecasting course

1.
2.
3.
4.
5.

II. We are trying to improve the design of the course. In the current situation of the course, we need your observations, feelings and thoughts. Can you argue among yourself about what do you think about this course?

APPENDIX II: Discrete Choice Experiment Form

Sayın Katılımcı, Bu çalışmanın amacı Dokuz Eylül Üniversitesi İşletme Fakültesi İşletme Bölümü (İngilizce) Lisans programına ait Business Forecasting dersinin tasarlanması sürecinde, siz öğrencilerin ilgili dersin özelliklerine yönelik tercihlerinizi belirlemektir. Çalışmanın sonuçları İngilizce İşletme Yönetimi Yüksek Lisans programında yürütülen bir tez çalışması kapsamında kullanılacaktır.

Çalışma iki bölümden oluşmaktadır. Birinci bölümde sizlerin demografik özelliklerinizin belirlenmesine yönelik sorular sorulmuştur. İkinci bölümde ise size yöneltilecek tasarım alternatifleri içinden seçim yapmanız istenecektir. Verilen alternatifler uygun değilse seçim yapmama şansına sahipsiniz. Vereceğiniz cevaplar tez çalışmasının doğru sonuçlar vermesi için büyük önem arz etmektedir. Bu sebeple soruları içtenlikle doldurmanızı rica eder, cevaplarınızın çalışma haricinde hiçbir yerde kullanılmayacağını belirtiriz. Zaman ayırdığınız için teşekkür ederiz.

Doç. Dr. Aysun KAPUCUGİL İKİZ (Dokuz Eylül Üniversitesi, İşletme Fakültesi - Tez Danışmanı) Merve GÜNDÜZ (Dokuz Eylül Üniversitesi - İngilizce İşletme Yönetimi Yüksek Lisans Öğrencisi)

Next

Cinsiyetiniz?

[▼]

Okuduğunuz bölüm kaçıncı tercihinizdi?

- ◯ 1-5
- ◯ 6-10
- ◯ 11-20
- ◯ 21-30

Sınıfınız?

[▼]

Daha önce QMT seçmeli dersi aldınız mı?

- ◯ Evet, artık almayı düşünmüyorum
- ◯ Evet, seçmeye devam edeceğim
- ◯ Hayır, ancak seçmeyi planlıyorum
- ◯ Hayır, sonraki dönemlerde de seçmeyi düşünmüyorum

Dersi ne zaman aldınız?

[▼]

Yıl Sonu Genel Not Ortalamanız Nedir?

GPA [ ]

Business Forecasting dersinin işleniş şekliyle ilgili elinizde sadece bu alternatifler olsa, hangisini seçerdiniz?

(1 of 14)

Teorik bilgi edinme	Hem sınıfta birebir, hem de online kaynaklı ders	Hem sınıfta birebir, hem de online kaynaklı ders	Hem sınıfta birebir, hem de online kaynaklı ders
Term project teslim sayısı	Tek teslim	Tek teslim	Tek teslim
Quiz Şekli	Online	Sınıfta	Sınıfta
Quiz vs. Final	Quiz var Final yok	Quiz var Final yok	Quiz var Final yok
Term project sunumu	Yok	Var	Yok
Term Project Kişi Sayısı	4 kişilik grup	2 kişilik grup	2 kişilik grup
Teorik dersin soru çözme olanakları	Hiçbir soru çözümü olmasın	Sınıfta soru çözümüne ek evde soru çözüm pratikleri yapılsın	Hiçbir soru çözümü olmasın
Grupların belirlenmesi	Hoca rastgele belirlesin	Hoca rastgele belirlesin	Öğrenciler belirlesin
	Seçimim	Seçimim	Seçimim

HİÇBİRİ: Bu seçeneklerin hiçbirini seçmezdim.

Seçimim

APPENDIX III: Kansei Engineering Experiment Form

Sayın Katılımcı,

Bu çalışmanın amacı Dokuz Eylül Üniversitesi İşletme Fakültesi İşletme Bölümü (İngilizce) Lisans programına ait Business Forecasting dersinin yeniden tasarlanması sürecinde, siz öğrencilerin ilgili dersin özelliklerine yönelik tercihlerinizi belirlemektir. Elde edilen sonuçlar İngilizce İşletme Yönetimi Yüksek Lisans programında yürütülen bir tez çalışması kapsamında kullanılacaktır.

Anket çalışmamız iki bölümden oluşmakta ve sorular İngilizce sorulmaktadır. Birinci bölümde sizlerin demografik özelliklerinizin belirlenmesine yönelik sorular sorulmuştur. İkinci bölümde ise sunulan tasarım alternatiflerinin sizde uyandırdığı hisleri tanımlayan kelimelerin seçimini yapmanız istenecektir. Ders alternatifi verilen kelime çiftlerinden hangisine daha yakınsa onu işaretlemeniz gerekmektedir.

Vereceğiniz cevaplar, tez çalışmasının doğru sonuçlar vermesi için büyük önem arz etmektedir. Bu sebeple soruları içtenlikle doldurmanızı rica eder, cevaplarınızın çalışma haricinde hiçbir yerde kullanılmayacağını belirtiriz. Zaman ayırdığınız için teşekkür ederiz.

Doç. Dr. Aysun KAPUCUGİL İKİZ (Dokuz Eylül Üniversitesi, İşletme Fakültesi - Tez Danışmanı)
Merve GÜNDÜZ (Dokuz Eylül Üniversitesi - İngilizce İşletme Yönetimi Yüksek Lisans Öğrencisi)

Next

What is your gender?

- ◯ Female
- ◯ Male

What is your grade?

- ◯ 2nd grade
- ◯ 3rd grade
- ◯ 4th grade
- ◯ Graduated

The first alternative of the Business Forecasting Course has the following features:

Obtaining theoretical knowledge: Face to face learning in the classroom
Problem solving opportunities of the theoretical lecture: In addition to problem solving session in the class, at-home practices will be also given.
Type of Examination: Midterm exam is a must. Instead of final exam a quiz will be held in the class
Attributes of Term Project: For the project, students will form their four-member groups on their own. The term project will be delivered in two parts and no presentation will be made for the project.

Business Forecasting Course Alternative 1

Obtaining Theoretical Knowledge:	Face to Face Learning
Problem Solving Opportunities	Lecturer solves problems in class and gives at-home practices
Type of Examination	Midterm
	In-class Quiz
	No Final
Term Project Features	Lecturer forms the groups
	Group of 2 people
	Term project presentation
	2-time submission of project

Please select appropriate option by sliding the circle between two extreme attributes below.

	highly close to the left	close to the left	between left and right	close to the right	highly close to the right	
abstract (soyut)						concrete (somut)
centralized (merkezileştirilmiş)						decentralized (merkezi olmayan)
individualistic (bireysel)						collaborative (iş birlikçi)
not satisfactory (tatmin etmeyen)						satisfactory (tatmin edici)
basic (temel)						advanced (gelişmiş/ileri)
not educational (eğitici olmayan)						instructional (eğitici)
non-effective (etkisiz)						effective (etkili)

non-interactive (etkileşimsiz)	interactive (etkileşimli)
disorganized (düzensiz)	organized (düzenli)
non-analytical (analitik olmayan)	analytical (çözümsel)

Back Next

0% 100%

APPENDIX IV: PLS Output for Kansei Words

Parameters			
Independent Variables	Dependent Variables		
	PC1	PC2	PC3
(Constant)	3.375	3.503	3.443
[inclass=no]	-0.094	-0.125	-0.083
[tboth=no]	-0.035	-0.054	-0.039
[online=no]	0.097	0.135	0.091
[pnone=no]	0.168	0.2	0.118
[pclass=no]	-0.035	-0.054	-0.039
[pboth=no]	-0.1	-0.11	-0.059
[examination1=no]	-0.097	-0.135	-0.091
[examination2=no]	0.097	0.135	0.091
[quiz1=no]	-0.094	-0.125	-0.083
[quiz2=no]	0.094	0.125	0.083
[termd1=no]	0.056	0.056	0.026
[termd2=no]	-0.056	-0.056	-0.026
[termn1=no]	0.056	0.056	0.026
[termn2=no]	-0.056	-0.056	-0.026
[terms1=no]	-0.039	-0.021	0.004
[terms2=no]	0.039	0.021	-0.004
[termp1=no]	-0.056	-0.056	-0.026
[termp2=no]	0.056	0.056	0.026

Independent	Dependent Variables								
Variables	k10	k9	k8	k7	k6	k5	k4	k3	k1
(Constant)	3.528	3.561	3.46	3.34	3.48	3.44	3.17	3.52	3.266
			8	2	5	3	7	3	
x_{11}	-.103	-.099	-.107	-.117	-.140	-.083	-.067	-.110	-.084
x_{12}	-.022	-.014	-.029	-.028	-.054	-.039	-.058	-.055	-.051
x_{13}	.094	.085	.102	.109	.145	.091	.093	.124	.101
x_{21}	.171	.162	.167	.181	.207	.118	.151	.193	.177
x_{22}	-.022	-.014	-.029	-.028	-.054	-.039	-.058	-.055	-.051
x_{23}	-.111	-.111	-.104	-.114	-.115	-.059	-.069	-.103	-.095
x_{31}	-.094	-.085	-.102	-.109	-.145	-.091	-.093	-.124	-.101
x_{32}	.094	.085	.102	.109	.145	.091	.093	.124	.101
x_{41}	-.103	-.099	-.107	-.117	-.140	-.083	-.067	-.110	-.084
x_{42}	.103	.099	.107	.117	.140	.083	.067	.110	.084
x_{51}	.050	.047	.045	.047	.050	.026	.063	.062	.070

x_{52}	-.050	-.047	-.045	-.047	-.050	-.026	-.063	-.062	-.070
x_{61}	.050	.047	.045	.047	.050	.026	.063	.062	.070
x_{62}	-.050	-.047	-.045	-.047	-.050	-.026	-.063	-.062	-.070
x_{71}	-.045	-.048	-.031	-.035	-.013	.004	-.026	-.028	-.042
x_{72}	.045	.048	.031	.035	.013	-.004	.026	.028	.042
x_{81}	-.050	-.047	-.045	-.047	-.050	-.026	-.063	-.062	-.070
x_{82}	.050	.047	.045	.047	.050	.026	.063	.062	.070