UNIVERSITY WEBSITE DESIGN WITH MULTIVARIATE STATISTICAL TECHNIQUES IN KANSEI ENGINEERING

Master Thesis

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ABSTRACT

UNIVERSITY WEBSITE DESIGN WITH MULTIVARIATE STATISTICAL TECHNIQUES IN KANSEI ENGINEERING

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In this age of advanced technology, every university has a website to endorse their programs and encourage students around the world to join one of their faculties. However, universities give much priority to the functionality and usability of their websites and they give less attention to meet the users' demands for visually attractive websites that satisfy their emotions.

This study proposes Factor Analysis (FA), Partial Least Squares (PLS) regression statistical methods and Kansei Engineering to identify elements of website design that are emotionally appealing to 18 - 37 age students in Turkey universities. A total of 22 Kansei words and 9 sample websites of Turkey universities are selected to investigate, 172 students consists of 84 females, and 88 males were asked to evaluate the selected websites using Kansei words (KWs). A 5-point semantic differential scale is used to evaluate the relationship between website elements and KWs.

Multivariate Statistical Methods such as FA and PLS regression were performed to explore the most influential KWs and the corresponding websites. The results showed the highest and the lowest rating websites, the website categories that have a positive and negative impact on students Kansei. The outcome implied that the FA and PLS regression and Kansei Methodology in this study played a crucial role in website design in terms of satisfying users' demands in this study.

Keywords: Factor Analysis; PLS regression; Kansei Engineering; Visual design; Kansei Words.

ÖZET

ÇOK DEĞİŞKENLİ İSTATİSTİKSEL TEKNİKLERLE KANSEİ MÜHENDİSLİĞİNDE ÜNİVERSİTE WEBSİTESİ TASARIMI

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Anadolu Üniversitesi, Fen Bilimleri Enstitüsü, Kasım, 2017

Danışman: Doç. Dr. Zerrin AŞAN GREENACRE

Bu ileri teknoloji çağında, her üniversite programlarını destekleyen ve dünya etrafındaki öğrencileri kendi fakültelerinden birine katılmaya teşvik eden bir web sitesine sahiptir. Bununla birlikte, üniversiteler web sitelerinin işlevselliğine ve kullanılabilirliğine çok öncelik verir ve duygularını tatmin eden görsel açıdan çekici web sitelerine yönelik kullanıcının talebini karşılamak için daha az dikkat verirler.

Bu tez, Türkiye üniversitelerindeki 18 - 37 yaş aralığında öğrencilerine duygusal açıdan çekici gelen, web sitesi tasarımı unsurlarını belirlemek için Faktör Analizi (FA), Kısmi En Küçük Kareler (PLS) regresyon istatistik yöntemlerini ve Kansei Mühendisliği'ni önermektedir. Türkiye'deki üniversitelerinden 9 örnek web sitesi ve 22 Kansei kelimesi araştırılmak üzere seçilmiştir, 84 kadından ve 88 erkekten oluşan 172 öğrenciye Kansei kelimeleri (KW'ler) kullanarak seçilen web sitelerini değerlendirmeleri için sorular sorulmuştur. Web sitesi unsurları ve KW arasındaki ilişkiyi değerlendirmek için 5 noktalı semantik farklılık ölçeği kullanılmıştır.

FA ve PLS regresyon gibi çok değişkenli istatistiksel yöntemler en etkili KW'leri ve ilgili web sitelerini açıklamak için tercih edilmiştir. Sonuç öğrencilerin Kansei üzerinde olumlu ve olumsuz etkisi olan web sitesi kategorilerinin en yüksek ve en düşük derecelendirmedeki web sitelerini göstermiştir. Web sitesinin tasarımında kullanıcının isteğini tatmin açısından bu çalışmadaki FA ve PLS regresyon ve Kansei Metodolojisinin çok önemli bir rol oynadığını bu tezdeki sonuç ortaya koymaktadır.

Anahtar Kelimeler: Faktör Analizi; PLS regresyon; Kansei Mühendisliği; Görsel tasarım; Kansei kelimeleri.

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Saed JAMA ABDI

07/12/2017

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with "scientific plagiarism detection program" used by Anadolu University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

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(Signature)

Saed JAMA ABDI

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LIST OF SYMBOLS AND ABBREVIATIONS

X_i	: Observable variable and predictors
μ_i	: Mean vector
Λ	: Vector loadings
Λ^T	: Transpose of vector loadings
F_i	: Unobservable variables (Factors)
ε_i	: Error term
$E(F)$	: The expected value of unobservable variables
$Cov(\varepsilon, F)$	: Covariance of the error term and factors
$E(\varepsilon F^T)$	: Expected value of error term and factors
F^T	: Transpose of factor
$E(\varepsilon)$	: Expected value of the error term
$Cov(\varepsilon)$	: Covariance of the error term
I	: Identity matrix
ψ	: Specific variance
λ_i^2	: Communality
σ_{jj}	: Total variability of the observable variables
Σ	: Covariance Matrix
S	: Sample covariance matrix
R	: Sample correlation matrix
$\widehat{\Lambda}$	: Estimated vector loading
$\widehat{\psi}$	: Estimated specific variance
Q_i	: Eigenvalues
e_j	: Eigenvectors
e_j^T	: Transpose of eigenvectors
$\hat{e}_m$	: estimated eigenvectors
$\widehat{Q}_m$	: Estimated eigenvalues
χ^2	: Chi square distribution
Y	: Response matrix
β	: Coefficient
t_k	: latent variables

p_k & q_k	: Loading vectors
W	: Weights
KE	: Kansei Words
SD	: Semantic Differential
KW	: Kansei Words
KES	: Kansei Engineering System
FA	: Factor Analysis
PCA	: Principal Component Analysis
CFA	: Confirmatory Factor Analysis
FA	: Factor Analysis
PCA	: Principal Component Analysis
CFA	: Confirmatory Factor Analysis
EFA	: Exploratory Factor Analysis
PLS	: Partial Least Squares
OLS	: Ordinary Least Squares
NIPALS	: Nonlinear Iterative Partial Least Squares
KMO	: Kaiser-Meyer Olkin
F1	: Factor one
F2	: Factor two

1. INTRODUCTION

In this modern age, the internet has become a global means of communication and has revolutionized the education system of the world. We live in a world where students and teachers are constantly more dependent on searching information from the internet and Google-searching machine, while universities use websites to endorse their programs and encourage students to join to one of their faculties.

Websites, which are a medium communication of universities, have become more important than ever. In today's world every university wants to attract more and more visitors, mainly students around the globe, by simply creating a website. However, as the university websites are swiftly increasing, most of the universities are establishing websites with a good design in terms of functionality and usability which is not enough to meet users' expectations and feelings.

The assumptions of many academic websites are based on the fact that the user spends a few minutes in order to find maximum information, irrespective of whether they like or dislike it, which means that the primary emotional responses of the users are completely ignored. While universities are prioritizing functionality and usability, the users are on the other hand demanding emotionally interesting websites and this is where the major challenges arise. For many years designers underestimated to take into account the emotional designs, but nowadays it has become a hot topic, hence many users are extremely demanding websites that are functional, easily usable and meet their emotions.

Emotion plays a crucial role in website design but only skilled designers perceive the significant appeal of emotions and use their artistic ability to avail of this appeal. Nevertheless, emotions have a little influential role in the designing field because many designers do not exploit it and instead they focus on functionality and usability.

In his book of emotional design norman (2004) mentioned that only usable products are not essentially pleasurable, he argued that usable and unpleasant products are harsh, this is a clear indication that universities need to create a pleasant and usable website in order to satisfy students emotional needs. To translate user's emotions and create an emotionally pleasant website is not an easy task. Norman stated that the critical need for methodologies and procedures supporting the incorporation of emotional facets into product design generates emotional design, which considers the complex emotional relationships connecting objects to individuals.

Website designers should consider a full range of user-interface issue and should work to develop the design of a website that fulfills human preferences in order to attain expectations. The first impression of websites is an important factor of grasping the user's attention and feeling (Lindgaard et al., 2006).

The assumptions of designers are that users will enjoy features on the website. Unfortunately, this does always happen. A vast majority of website users moves from one website to another if the website does attract their attention at first sight. This indicates that the first impression of someone is influenced by the appearance of a website because if users feel unsatisfied with the website, they will abandon it and turn to others (Parush et al., 2005).

On the other side, one of the crucial (if not the most crucial) characteristics of a quality website design is the visual design (Al-salebi, 2010). A well designed website attracts the users' attention and feeling while terribly designed websites frustrate visitors. However, creating a good visual designed website needs to give much priority to the user's feelings towards the attractiveness not only usability.

Al-salebi divides the characteristics of a good website into three main parts, namely visual design, readability, and contents. Visual characteristics of good page layout, good navigation, consistency, picture and careful selection of color features contribute to the enhancement of the website appearance.

Poorly designed websites provide little value no matter how good and easy the functionality and usability of the website and how clearly organized the information needed by users. According to Song et al. (2012) website design is a very composite procedure that involves multiple technologies and knowledge, and one of the most important skills of website designers is to produce a functional site that also captures the user's desired emotions and pleasure.

Grouping related elements, and ensuring all essential information is accessible without showing redundant information is what makes users satisfied. However, website designers should present information in a well-structured manner that reflects the user's needs in order to prevent the chance of users becoming frustrated.

Based on human needs Song et al. (2012) have described a hierarchy pyramid to illustrate what type prospects (expectation) products should meet by giving highest priority to functionality and usability and then to the user's pleasure (see Figure 1.1).

According to Song et al., functionality satisfaction is the fundamental core of a product. Without functionality, it is impossible to use any kind of product. The second fundamental core of human needs from a product is usability. Thus the ability to use a product easily and understandable way that can prevent the users to get frustrated.

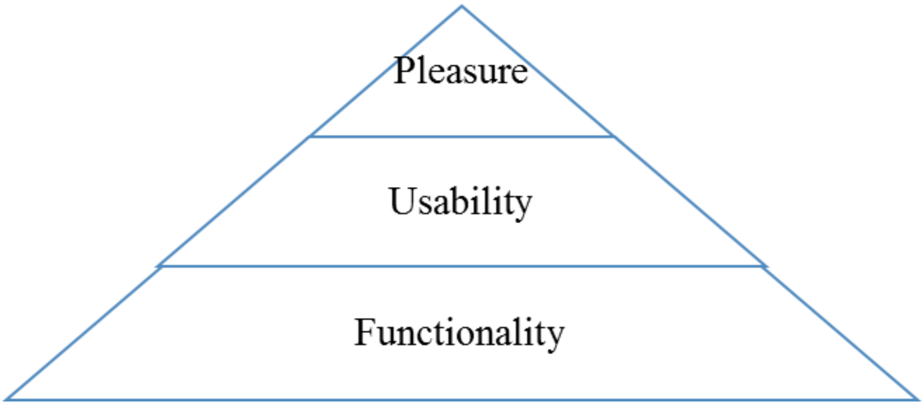

Figure 1.1. *Hierarchy Levels of Human Needs (Song et al. 2012)*

The third and final level of expectation of users from a product is the pleasure, namely the emotions and feelings that products give users. Functionality and usability of product are not aspects of deciding how pleasurable products are to use (Jordan, 1998). Jordan defines the pleasure in the product as "the emotional and hedonic benefits associated with product use."

Therefore, a website that brings positive emotions to users must meet all three levels proposed by Song et al. However, the first two levels (functionality and usability) can be easily improved, but the level of pleasure is difficult to achieve even though increasing attention is being paid to the emotional aspects of website design. There is no systematic method of determining design concepts and details but Song et al. (2012) have made an attempt to engineering emotion in website design using Kansei Engineering (KE).

A well-designed website should not only meet the basic requirement of functionality, but also require appealing to the user's feelings at first sight. With this aim in mind, KE, which prioritizes satisfying the user's feelings and needs, has attracted much attention. Zhai et al, (2009) stated that statistics play an important role in Kansei Engineering because varieties of statistical methods are used in this field. Focus group discussions and interviews are the most widely used qualitative methodologies. Although they give substantial information on emotion elicited by a product, they have plenty of weaknesses and difficulties; results are influenced by a person's experience, they need much time and obtaining guidelines about product design can be challenging because users are not thinking in a designer's paradigm. However, quantitative methodologies overwhelm some of these challenges and difficulties.

Kansei Engineering is a quantitative method used in the emotional design and frequently based on the use of a questionnaire. The purpose is to find out the parameters of a product that are evoked by the chosen emotions. Kansei Engineering is based on collecting qualitative data and users usually make ratings. When data are collected, statistical techniques are used to connect the properties of a product to the evoked perceptions. Due to the extensive need for collecting and analysing data in order to reach conclusions, it seems that statistics plays a major role in KE.

However, selecting appropriate statistical methods and presenting results in an easily understandable approach is another problem for product designers. Most probably only statisticians can deal with this problem.

Despite many industries utilizing Kansei engineering and using statistical methods for product design, website designers, particularly academic website designers, do not interact with this field widely. Even though there are some previous studies, Kansei Engineering is not very popular in Turkey.

This study is motivated by the extensive need of developing the Kansei engineering approach that is really perfect in establishing the knowledge between human Kansei and design elements of an academic website by utilizing multivariate statistical analyses.

The structure of the study is organized as follows. Chapter 1 emphasizes the introduction together with literature review based on the objectives of the thesis. Chapter 2 presents the history of KE, types of KE, model building, and measurements of Kansei engineering are discussed deeply.

The third Chapter provides details of methods and the methodology of the thesis such as research framework, instrument, and procedure we used, sampling technique and data collection method we used. Furthermore, the objective of the study, significance, and limitation of the study are included in this chapter.

Chapter 4 indicates statistical methods used in study and their interpretations while Chapter 5 demonstrates findings and discussions of the study, conclusions we have achieved, recommendations we provided and how this addresses the aims and objectives of the study.

2. KANSEI ENGINEERING

The purpose of this chapter is to discuss and describe in detail the definition of Kansei engineering, types of Kansei Engineering, its uses and the relationship between Kansei Engineering and Multivariate Statistical analyses.

The term “Kansei” is originally a Japanese word that is used to indicate human feelings and impressions towards a particular product, artifact, and surroundings. According to (Lokman et al., 2008), it is very difficult to translate the term to other languages because it is deeply related to Japanese culture, however, Lokman described a situation or mental state in which sentiments and feelings are harmonized. When the term interacts with other cultures, Kansei means the sense and sensitivity that elicited subjective pleasurable feelings from the interaction with an artifact (Nagasawa, 2004).

Kansei Engineering is considered a technology that connects people’s Kansei into product design in order to produce products that satisfy user’s expectations, and was founded by Prof. Nagamachi at Hiroshima University in the 1970s after he identified that companies are interested to quantify the user’s impression of their products. KE integrates Kansei and Engineering to grasp human Kansei (emotions and feelings) towards an existing or under development product design in order to produce products that users will enjoy and satisfy them. The purpose of KE is to exhibit the Kansei value of products that prompts the emotional responses

Kansei engineering is a methodology of relating to customer’s Kansei with existing products or prospective product’s design (Bakaev et al., 2016). The Kansei Engineering is interpreted variously Lee et al. (2000) have classified the meaning of a Kansei word into five main aspects, as shown Figure 2.2.

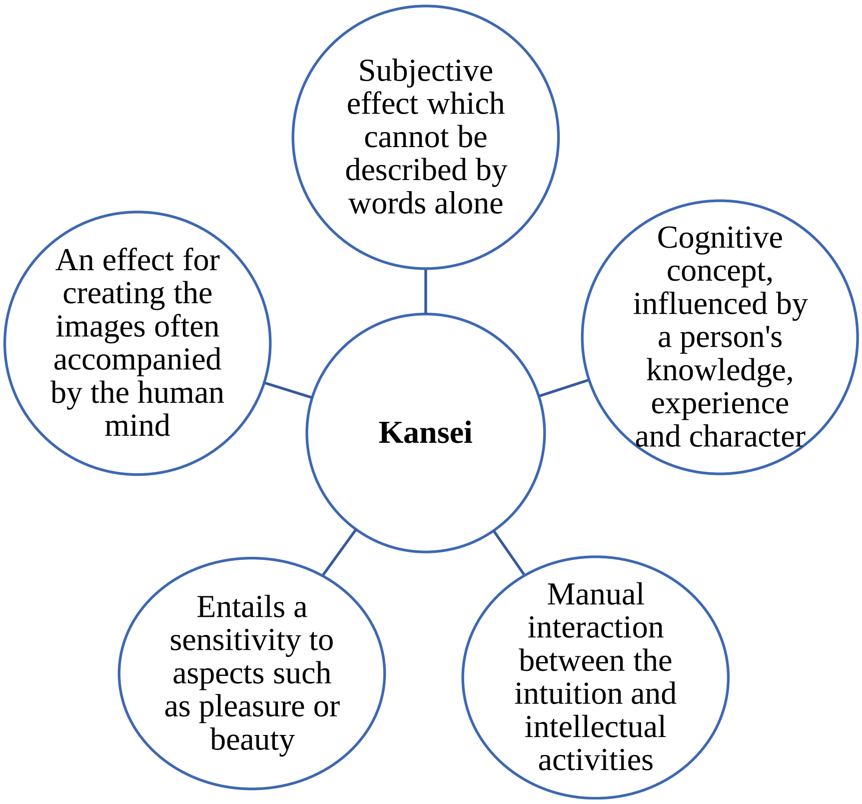

Figure 2.2. *Classification of Kansei engineering (Song et al., 2012)*

Song et al. (2012) argued that KE represents a systematic method of gathering people's feelings and emotions towards a product's design through a series of physiological and psychological measurements. Even though a user's KE is influenced by people's experiences, knowledge, and personality that differs from one person to another, KE begins with the collection of sensory related functions such as hearing, vision, taste, smell, and touch.

2.1. Types of Kansei Engineering

The previous section we discussed that KE is a set of techniques and methods used to measure the user's feelings and emotional expressions to certain product properties in order to design the products in a way which applicable user's expressions, whereas in this section we will focus on the types of KE. So far, there are six different types of KE which have been proven and tested (Schütte, 2002b) and the last three are very complex. We will explain each type in the easiest way without giving long details.

2.1.1. KE type 1 – category classification

Category classification is the first type of KE, which is the simplest and quickest way to make the Kansei analysis (Schütte, 2002a). Generally, this kind of KE involves using expressions known as Kansei Words (KW) that have links to the product. Kansei words are generally adjectives or verbs representing emotions, and then it would be arranged to 5-point Semantic Differential (SD) scale.

To create a specific product that matches people's Kansei, this method breaks down the Kansei category of products into a tree structure to identify the design details as shown in Figure 2.3. The division would help to get a sub-concept to accomplish the identification we want. In this method, people usually use a questionnaire to express their feelings and emotional design toward the target product.

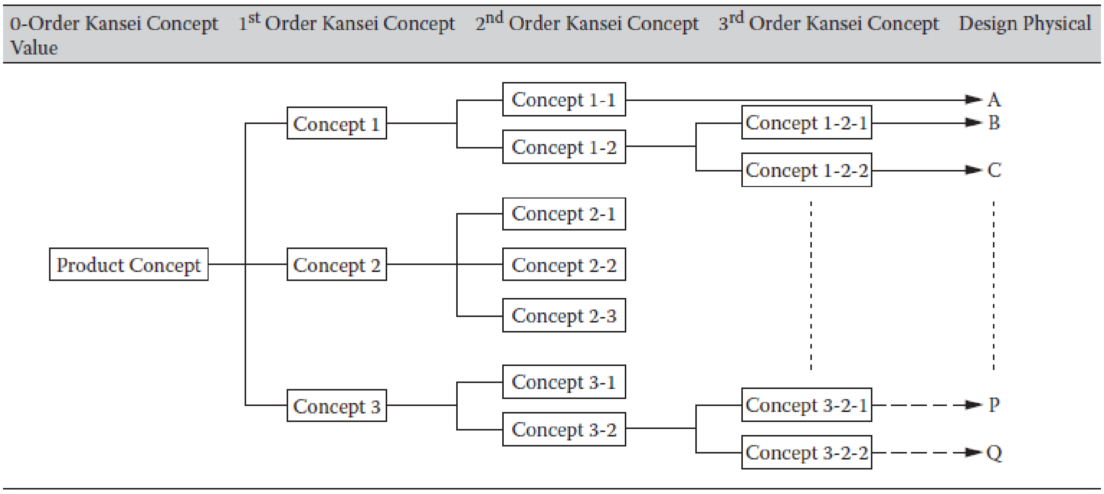

Figure 2.3. *Concept of type 1 KE (Nagamachi & Lokman, 2003).*

The purpose of category classification is to translate the verbal product description of the human into detailed design and to help designers to invent the design elements that make the product better fit human feelings.

Nagamachi & Lokman (2011) recommended to follow a five-step process while performing type 1 KE. The first step is identifying of target people who are expected to use the product, and then determining product concept and breaking down the product concept into simpler sub-concepts.

The fourth step proposed by Nagamachi and Lokman is the development of physical characteristics of the product, this will help designers to decide how the new product will look like, and the final step is the translation of physical characteristics into technical specification.

2.1.2. KE type 2 – kansei engineering system

Kansei Engineering System (KES) is a computer-aided method of mapping the people's Kansei to the product properties. KES method indicates the computer application of the KE type I because when the people's Kansei was recognized through Kansei adjective, the information is stored in a computer database to link Kansei words with the properties of the product that were analyzed (Gaspar et al,. 2013). This enables designers to fully understand the impression and perception of the people so that product and guide designers can make decisions closer to what users want.

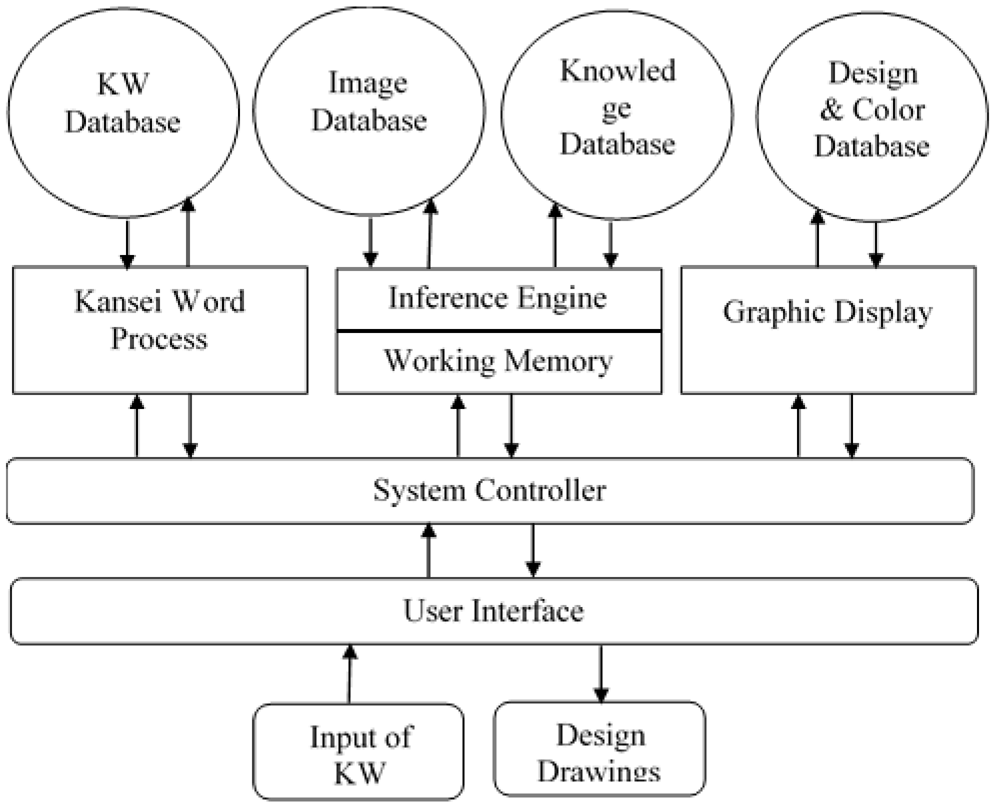

Figure 2.4. *KES databases (Nagamachi, 1995).*

As shown in Figure 2.4, KES consists of four separate databases which are Kansei Word database, Image database, Knowledge database and finally design and color database (Nagamachi, 1995).

According to Nagamachi (1995), the Kansei words database composed of words (Adjectives) that represents users feeling about a product which are collected from different resources such as magazines and literature. After that, a semantic differential (SD) scale questionnaires is constructed, then multivariate statistical analyses mainly Factor Analysis (FA) is used to analyze the data. The FA results suggest the Kansei word meaning space, from which the Kansei word database is constructed into the system.

In Image Database, it is essential toanalyse the semantic differential scales by using Quantification Theory Type 1 (QT1) (Hayashi, 1976), that is a Multiple Regression Analysis type of qualitative data. Then, we will find a list of statistics that relate Kansei word and product properties. The third database that is the knowledge database, composed of rules essential to decide the items correlated to the design and color and Kansei words established. Finally, in design and color database, the detail of product properties that involve or relate colors and designs are assigned to place in database differently. Then, the combination of design details and color are set by the system database that enables visualization of graphs of analysis.

2.1.3. KE types 3 – hybrid

The type 3 Kansei Engineering is known as Hybrid KE and consists of both Forward Kansei Engineering (Hsiao & Wang, 2012) and is similar to that of type 2 because a computer-assisted system is important to use. As shown Figure 2.5, the upper arrow from the left to the right indicates Forward Kansei Engineering and the lower arrow from right to the left show Backward Kansei engineering.

In case of forward Kansei engineering, is the KES in which people usually choose the product that matches their feeling. After people indicate the Kansei they have in their mind, then computers are used to expose the design that best fit to their Kansei. The chosen products are assessed from people's opinion by using opposite adjective known as Kansei Words. In the backward Kansei Engineering, is the KES in which the designers draw products in their mind then a computer-assisted system is loaded.

The computer identifies the shapes and patterns of the products will appear (Matsubara & Nagamachi, 1997). Finally, an example of Hybrid KE was used by Wang (2011) for his article "hybrid Kansei engineering design expert system based on grey system theory and support vector regression" in which he examines the relationship between customer's design and product form.

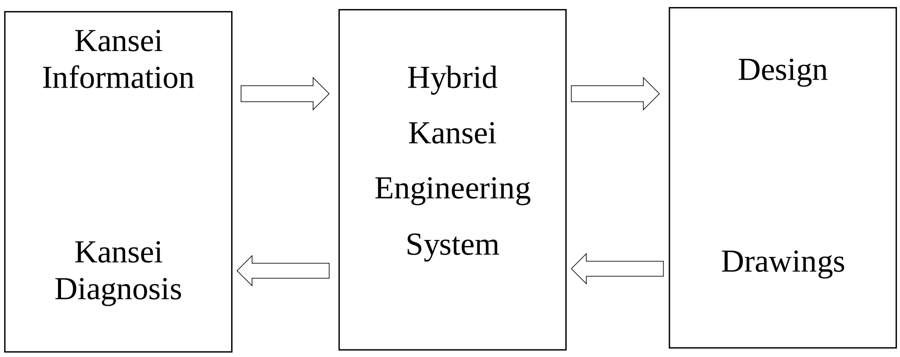

Figure 2.5. *Hybrid Kansei Engineering System (Hsiao & Wang, 2012)*

2.1.4. KE types 4 – mathematical

Mathematical Kansei Engineering, also known as Kansei Engineering modeling, constructs a mathematical model in order to assess the human feelings and perceptions using a series of words known as Kansei words and computerized system.

This type of Kansei Engineering can be reached by using the following four steps. The first step is identifying the attributes of the Kansei; the next is obtaining data essential for Kansei, followed by specifying user's preferences and finally aggregating performance of prioritized goals (Yan et al., 2008).

2.1.5. KE type 5 – virtual

Virtual Kansei Engineering is an advanced technology capable of constructing a virtual space and provides an experience that is not possible to have in the real world. The main characteristics of KE type 5 is the use of this technology by building a space and adapting it to the feeling of the users. Thus, it is not possible to provide an experience to examine the approach to the design of a proposed Kansei expected by the people.

It is very useful and efficient for the product of a large scale because it is possible to analyze the virtual space before producing it physically and combines KE system and virtual reality technology. Example of virtual Kansei Engineering was used (Anzai & Ogawa, 1995) to satisfy their customers' feelings toward a kitchen system by showing the complete kitchen with material and decoration. According to Anzai & Ogawa, the customers are allowed to touch and see kitchen components in the virtual space.

2.1.6. KE type 6 – collaborative

This is a type of KE in which designers from different places work together in order to design a product via internet. Each and every designer offer his/her idea about how the new product will look like, then designers discuss and finally propose a new product design (Nagamachi, 2002). In Collaborative Kansei engineering, designers come together in a meeting and discuss specification of the product, and then they depart during product development process, the designers exchange ideas by using the internet as means interaction between designers.

Collaborative KE makes a design work effective and efficient. However, (Cho et al., 2011) believe that this type of KE is efficient when and where availability of Internet and technologies are possible, otherwise, it is impossible for the designers to exchange views and obtain user's perception.

2.2. Measurement of Kansei

Kansei Engineering is a quantitative statistical method that depends on the collection of numerical data, even though the compilation of data to describe the phenomenon is not easy. Nevertheless, a collection of accurate data is crucial because incorrect data will lead to erroneous conclusions. In order to find a good measurement system, validity and reliability of data are used many times.

Simply, validity is the extent to which a test measures what we want to measure (Thatcher, 2010). It gives us the closest approximation to the truth and can be divided into different parts. From a statistical point of view, validity is having unbiased estimators of reality. Reliability is simply consistency, which is the degree to which a test consistently measures whatever it measures. Figure 2.6 gives us good understanding.

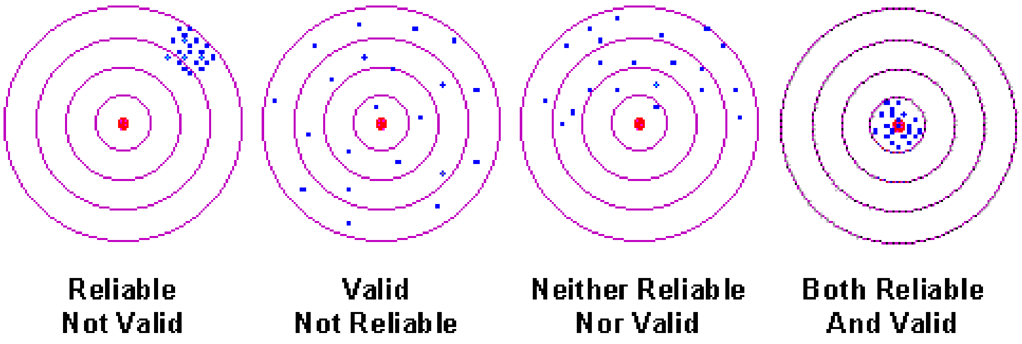

Figure 2.6. *Validity and reliability measurement system*

According to Lokman, Kansei measurement is a process of grasping customers' emotions and feelings and it is very difficult to measure it (Lokman, 2010), that means understanding user's Kansei is always challenging because it depends on the person's preference, moods, attitudes and interpersonal stances which are complex structures and requires sensitive measuring instruments. Unluckily, even using the most sophisticated and powerful measurement does not lead us to grasp the Kansei of users completely.

However, the questions that come in our mind are how do we know the sort of Kansei a user feels towards a target product?. And how can the user's Kansei be grasped and transformed into an understandable information that is essential for the development of a new product or renovating an already existing product in order to satisfy users.

Currently, there are no exact ways to measure Kansei directly because Kansei is by its nature ambiguous but according to (Nagasawa, 2002a) there are two methods of measuring emotions indirectly and Figure 2.7 give more details.

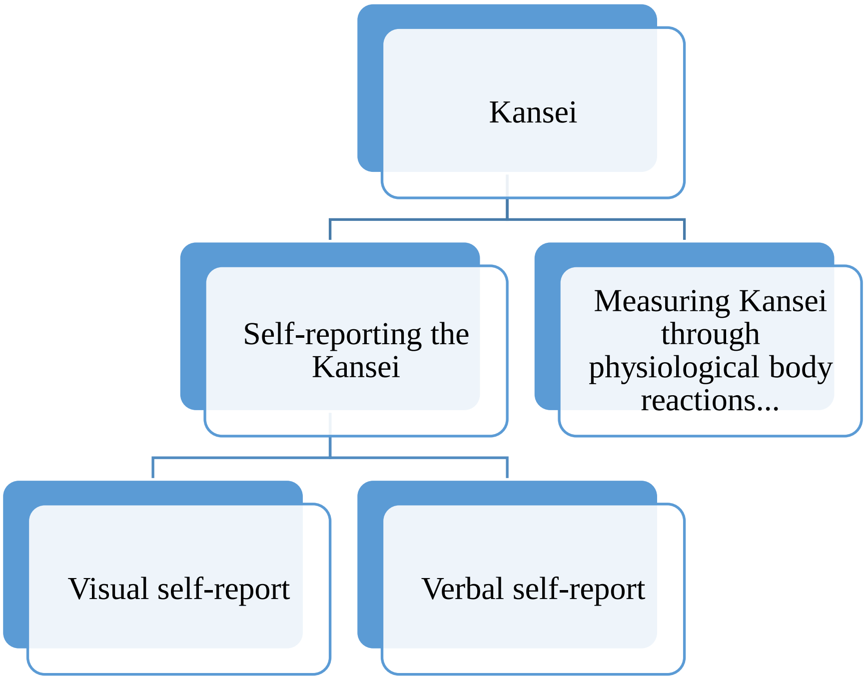

Figure 2.7. *Methods of measuring the Kansei (Nagasawa, 2002a)*

According to the above Figure, KE can be measured indirectly using two different methods which are 1. Measuring Kansei through physiological body reaction and 2. Psychological self-reporting the Kansei. The latter is then sub-divided into two parts (2a) images self-report form and (2b) verbal self-report form. According to Nagasawa, measuring Kansei through physiological body reaction is a process that aims to capture a user's behavior, responses and body expressions and can be measured using analyses of brain waves (EEG) electromyography (EMG), electrocardiogram (ECG), eye movements and other instruments. However, for our study, the Psychological self-reporting the Kansei type of measurement will be used, particularly the verbal self-reporting.

2.2.1. Self-reporting the kansei

Self-reporting the Kansei is a subjective evaluation system and its used a semantic differential scale to measure a user's emotions and feelings for a product. A questionnaire form with scale range is prepared by using either words or images. In this day and age people prefer filling out of a form instead of using images that describe emotional expressions, but both methods are suitable and have advantages.

As the above Figure 2.7. shows, there are two kinds of self-reporting techniques for measuring the Kansei; verbal self-report and visual self-report. In the verbal self-report, survey participants are asked to evaluate their Kansei orally by using open-ended questions or by ranking different words conveying emotions by means of semantic differential or Likert scale questions (Kong & Yang, 2009). In visual self-report, instead of relying on the use of words the rating is done by using various cartoon-like animating images representing various emotions (see figure 2.8) but generally, rating by using words is the most popular one.

However, both methods have problems that need to be addressed in order to avoid reaching erroneous conclusions. Using a visual tool of self-reporting, cartoons representing emotions can be interpreted differently due to cultural difference. On the other hand, verbal self-reporting of emotions linguistic problems are sometimes met because some words may have indistinguishable meaning to some participants.

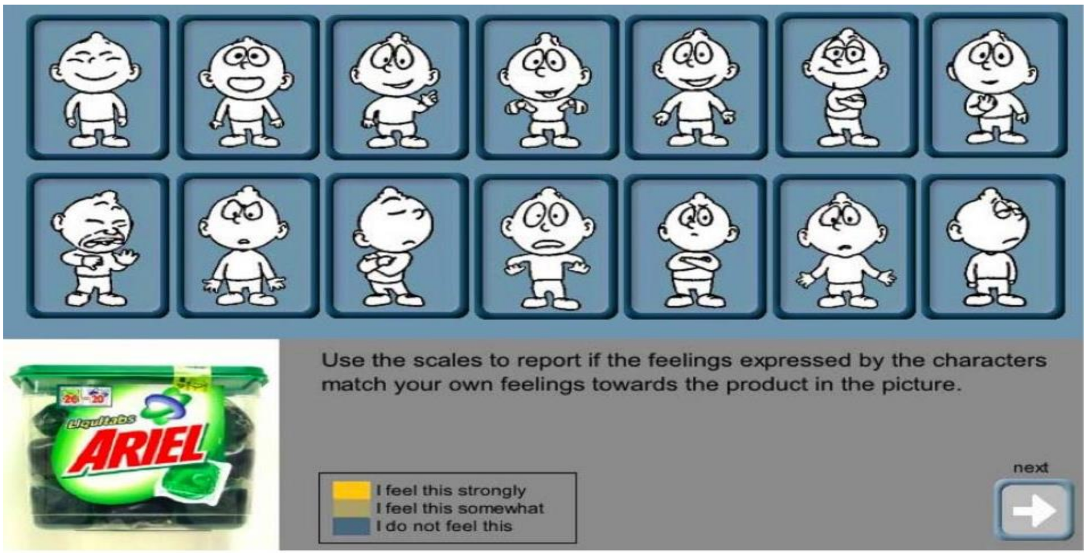

Figure 2.8. *Cartoon-like images representing various emotions*

The above Figure 2.8 illustrates a non-verbal self-reporting tool that measures different (pleasant and unpleasant) emotions known as a Product Emotion Measurement Tool (PrEmo) and was developed Pieter Desmet in 2002. PrEmo composed of 14 animations in which each represents a specific emotion.

The first seven PrEmo represents positive emotions (desire, pleasant surprise, aspiration, amusement, admiration, satisfaction, and fascination) and another seven negative emotions (indignation, contempt, disgust, unpleasant surprise, dissatisfaction, disappointment, and boredom). Finally, PrEmo can be used as a quantitative tool (e.g. to recognize the perception with the most pleasant impact) and as a qualitative tool of data analysis (e.g. to use as a conversation instrument in user or customer interview).

2.3. The Structure of Kansei Engineering

The structure of KE depends on the purpose and context of individual research, different types of KE models are used in various perspectives, however, there are similarities in the procedures used for evaluation. Simon Schütte was developed a general model used in KE (Schütte, 2007) after he examined various kinds of Kansei Engineering. The model is presented in Figure 2.9.

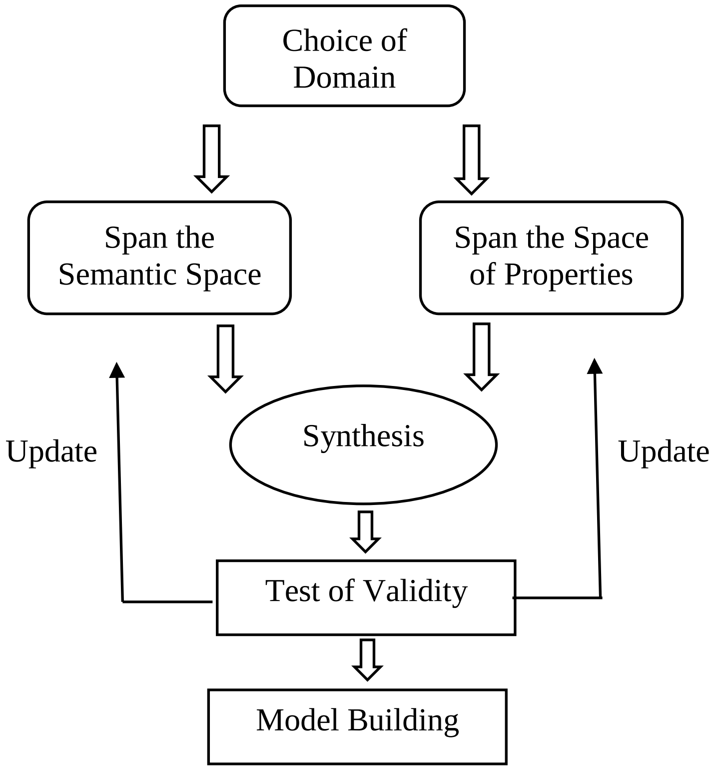

Figure 2.9. A *general Model of Kansei Engineering (Schütte, 2007)*

This model proposed by Schütte composed of a six stage process and various methods can be used within each stage. After the selection of a domain , the product can be defined by semantic and product properties. In the synthesis phase Semantic and Product Properties are connected together. After synthesis, a validity test is done and finally statistical model is developed.

2.3.1. Choice of domain

Selecting the domain refers to the target product under the study (Ingrassia, 2008) and in general, it gives a description of the product type. The domain can be a tangible or intangible product, existing product and design solution that is not yet known. The definition of targets group (our case websites designs) and user type includes the choosing domain.

2.3.2. Span the semantic space

Kansei Engineering is an internal feeling that is very difficult to measure directly and it is not simple to grasp the human Kansei. The Semantic Differential (SD) scale method was first proposed by (Osgood, 1957), in an attempt to describe products (domains) by certain expressions.

The Spanning of Semantic Space can be categorized into three stages. The first one is gathering a large number of words that describing the products (domains). These words can be collected through the use of suitable sources such as the internet, magazines, manuals, experts, ideas, etc.

According to Ingrassia (2008), based on the product you are considering to investigate, the number of words gathered vary from 50 to 600, but Schütte (2007) argues that these words vary from 100 to 1000 words in order to prevent information loss. Nevertheless, there is no commonly agreed number of Kansei words, all is based on the availability of Kansei words and the extent of the study.

The second stage is to group the words. In here the goal is to pick up the expressions (words) with the highest influence on the people's (human Kansei). There are two methods that can group words based on the existing context.

- ⇨ Manual selection (e.g. Affinity Diagram, choices of designers)
- ⇨ Statistical methods (e.g. Principal Component Analysis, Factor Analysis, Cluster Analysis)

Third, after words are organized a few representing words are picked up from this spanning the semantic space and they are called KWs. Kansei words are adjectives selected from people describing their Kansei (feeling) toward a particular product (domain).

2.3.3. Span the space of properties

The examination of Span the Space of Product Properties provides a variety of activities equivalent to that of the semantic space. The core aim of this part is to gather all aspects representing the chosen domain and select attributes which have high impact on user's emotion and choose products representing the selected product properties before the data is collected for the synthesis phase (Schütte et al., 2004).

Different resources such as user's advice, literature, and existing products etc. can be collected products represent the domain. Generally, choosing properties that users wish to meet can prevent the Kansei interview to become inconvenient.

2.3.4. Synthesis

Using Statistical techniques, a link between Semantic Space (KWs) and the Space of Product Properties (Product's items/categories) is established. For every Kansei word, a number of product properties are found that affect the Kansei word. Nowadays, there are a number of qualitative and quantitative tools used. Since the incoming data is stacked in a standardized way several tools can be used and results are compared to reveal the most suitable tool. According to (Nagamachi, 2016) the number different tools available can be organized into two categories;

- Statistical Methods (e.g. Regression Analysis, Generalized Linear Model, Qauntification theory type I)
- Other Methods (e.g. Fuzzy Set Theory, Rough Set theory).

2.3.5. Test of validty

Factor analysis (FA) and Principal component analysis (PCA) are used to locate the Kansei words on the first principal components. FA and the PCA can be used to locate

Kansei words (the responses) on a scatterplot with the first principal components, so showing which responses are perceived as similar.

In this phase, it is also used to check data from the synthesis phase to see whether the distribution of data is normal or not. To do so, one sample t-test, Kolmogorov-Smirnov test and visual checking of distribution methods are generally used.

2.3.6. Model building

When the validity of the test shows adequate results, then the data collected from the synthesis can be shown as a model and it can mathematical or non-mathematical.

$$Y_{Kansei} = f(Product\ Properties)$$

The models presented depend on the product properties and forecast the Kansei score for a certain word. Based on the context of the research the function linear or non-linear.

3. RESEARCH METHODOLOGY

3.1. Research Framework

This Chapter illustrates the theoretical framework of the study as shown in Figure 3.10 and provide a description of the model. The study proposes Kansei Engineering that is a simple way of selecting products in a particular domain and then using Multivariate Statistical analyses. Even though there are different kinds of Kansei Engineering as we discussed in Chapter 2, the study utilizes Kansei Engineering type 1 to be the most suitable to be implemented into the model.

The model starts with the identification of our target product properties, then selecting appropriate Kansei words to measure participant's impression. The next step is mapping participant's Kansei to physical website properties in order to determine the association between Kansei and website design.

We divided the research model into seven stages. We developed Kansei expressions or words about website designs using a questionnaire to quantify the user's perception and feeling on universities website homepages. Initially, we selected universities websites as a domain of investigation followed by Kansei words about the student's feelings towards universities websites, and then we decided items and categories of universities websites designs.

To grasp student's Kansei, we collected website domains from Turkish universities websites. The selected website domains were classified based on their different items and categories. Some of the items considered include header color, font size of the title, logo, and some other categories.

A large set of Kansei words related to the website design items/categories was then collected and further investigations were made to determine words that exactly related to the selected attributes of the website designs. We analyzed two distinct sets of data: the website designs elements collected from the selected domains and student's feelings towards the selected universities websites to investigate the relationship between Kansei words and website designs.

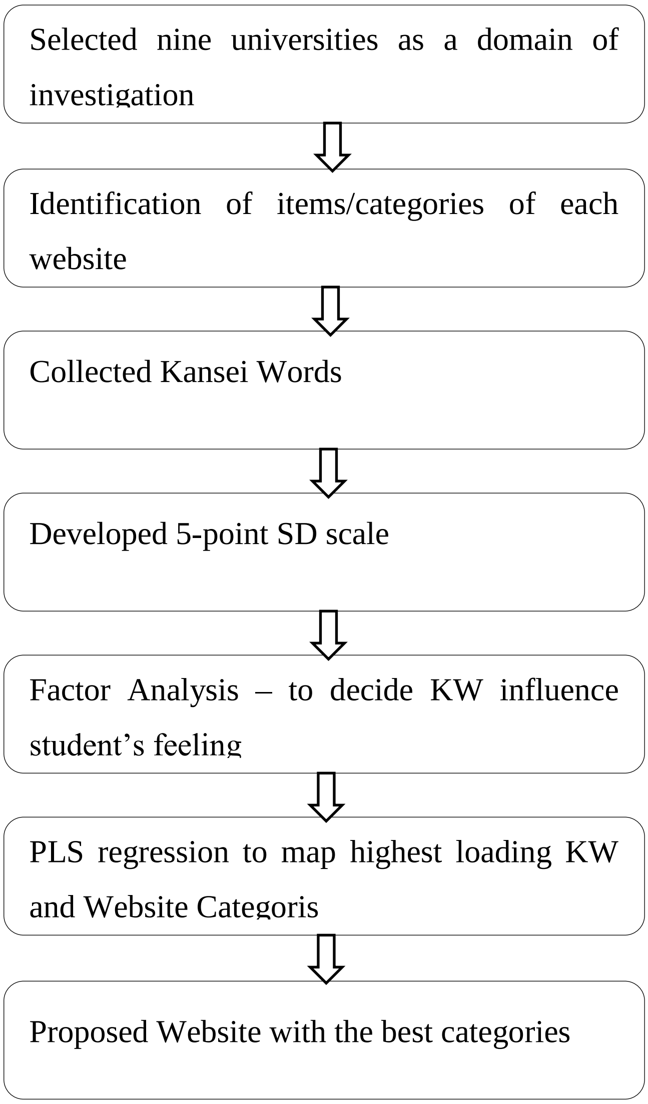

Figure 3.10. *Research Method*

We used multivariate statistical methods to analyze data and finally, we proposed a general design outline based on student's perception. This will help the designers to design a Kansei University website based on student's satisfaction. We conducted student's Kansei towards the appearances of universities websites and website design elements. The student's Kansei and website designs were then analyzed independently. As Table 3.1 shows, background color, pictures, the location of the logo, etc. are included some of the items/categories we considered.

Table 3.1. *Classification of Items/Categories*

Physical Traits of Websites		
	İtems	**Categories**
Header background	Color	White, Dark blue, Orange, Blue, Grey.
Logo	Location	Left, Centre, Right
Title font	Size	Small, Medium, Large
Header	Size	Large, Small, Medium
Footer	Size	Small, Medium, Large
Footer	Color	White, Blue, Yellow, Black
Top menu	Existence	Exist, not exist
Body background	Color	Grey, White, blue,
Main text font	Color	Black & White, Blue & White, Blue, white and Green
Total pictures	Number	1 – 5 pictures, 6 – 10 pictures, 11 and more pictures
Small pictures	Number	0 – 5, 6 and more
Large pictures	Number	0 – 1, 2 and more
Medium pictures	number	0 – 4, 5 and more
Video button	Existence	Video button, no video button

3.2. Research Instrument and Procedure

Initially, we manually selected top 150 Turkish Universities based on 2016 “Ranking Web of World Universities (http://www.webometrics.info/) and included both public and private universities.

Based on their visible appearance differences we selected nine websites (eight public universities and one private university). These websites have different visual homepage designs in terms of layout, colors, pictures and this is what gives students a general impression of the whole website.

Names and logos of the universities were removed from the questionnaire so that its status does not bias the respondent’s emotional responses of the websites. Even though the selected websites have an English version that is not different from the Turkish language version but the native language was not changed.

Figure 3.11. *Snapshot of websites used for Kansei survey*

3.3. Collection of Kansei Words

A total of 76 words that describe the visual design of websites were collected from magazines, users, designers and internet sources. In this step, no analysis has been made, but instead, we gathered related words. We made further analysis and reduced the Kansei words to 22 as shown in Table 3.2.

We remove words that have the similar meaning or at least very close in terms of meaning. These are the most appropriate Kansei words that describing the visual design of websites. Kansei words such as adorable, elegant, exciting, beautiful, appealing, well-structure, informative, etc. were included the Kansei words we selected in order to evaluate website designs. Before we start data collection, the board of ethics of Anadolu university verified the suitability of the KWs we used, and the selected best KWs were as follows:

Table 3.2. *Collection of Kansei words*

Sade (Plain)	Hoş görünümlü (Pleasant)	Zarif (Elegant)	Organizeli (Organized)
Sevimli (Adorable)	Moda (Fashion)	Düzenli (Orderly)	Şık (Stylish)
Memnun edici (Satisfied)	Modern (Modern)	Heyecan verici (Exciting)	Yaratici (Creative)
Güzel (Beautiful)	Çekici (Appealing)	İyi yapılandırılmış (Well-structured)	Son derece iyi (Outstanding)
İlginç (Interesting)	Renkli (Colorful)	Bilgilendirici (Informative)	Zevkli (Enjoyanble)
Muhteşem (Magnificent)	Gözalıcı (Eye-catching)		

3.4. Questionnaire Development

The questionnaire was prepared to investigate the student's preferences towards the 9 samples of selected websites. To obtain a quick answering opportunity and minimize the loss of information, we decided to organize the 22 pairs of Kansei words into 5-point semantic differential scale (Appendix).

To minimize the loss of information, the 22 pair of Kansei words and the samples of website images are put together side-by-side on one page and then printed with color (see Figure 3.12). The questionnaire is prepared to examine student's preferences to various university websites. The questionnaire was originally a Turkish language but we translated to English during the data entry phase using English Turkish online dictionary (Tureng) and language expert consultant.

To investigate students emotional implicit nine representative sample of different universities websites with 22 different Kansei words related to the website designs were selected. The demographic questions composed of four questions, which are gender, academic year, the universities in which students belong to and where they live in. All these questions were multiple choice.

The questionnaires were distributed to the students and asked to rate their feelings towards each website. The first five questions were demographic while the rest of the questions were related to students Kansei towards website designs.

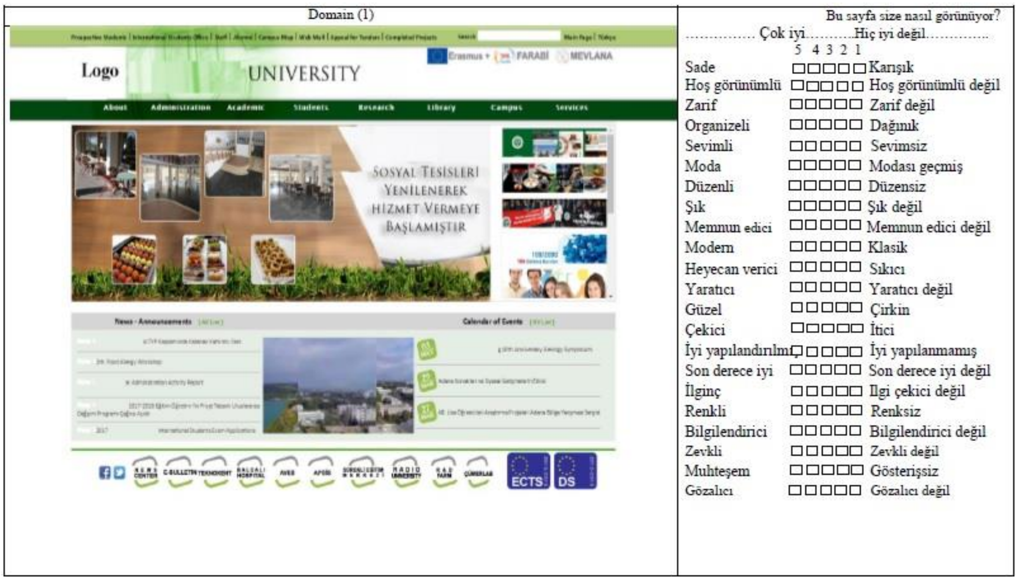

Figure 3.12. *Screen-shot of questionnaire we used*

3.5. Sampling Technique

In our study, it is used non-probability sampling; we decided that the convenience sampling technique is the easiest, cheapest, and the least time-consuming way to do our survey and to get more information within a short period.

The target population of the study was the students who participated 14th international Statistics colloquium held at Anadolu University on April 21-22, 2017. These students who come from different universities in Turkey accepted to participate the study.

3.6. Data Collection Method

To evaluate student’s Kansei towards websites, a questionnaire form was used to collect the data. After the opening speech of the colloquium on April 21, we started on the distribution of the questionnaire to the students before and after every session. The questionnaires were then collected at the end of the colloquium on April 22. To evaluate student’s Kansei we distributed 200 questionnaires and 172 of them were completed, while others were not returned or had more than 5% missing data.

Before the students started filling in the questionnaire, we gave each student a brief introduction to Kansei words and website images. For further simplification, we showed student's that the 5-point SD scale represents the scores from 5 (highest rate) to 1 (lowest rate). Finally, SPSS 23 (Statistical Package for Social Science) and XLStat software were used for the analysis.

3.7. Objectives of the Study

To develop an attractive university website, student's feelings must give priority. However, the questions that have been asked many times is how to make university website desirable on the base of emotion?

To answer this question, the objectives of the study are to investigate the relation between the visible appearance of websites and student's feeling of it. To determine most influential Kansei words to the website design, to examine the relationship between most influential Kansei words and the design item/category of websites, and to finally propose categories that have the strongest positive influence in students.

3.8. The Significance of the Study

Today websites become indispensable for every institution and organization. It is commonly agreed that aesthetic appearance plays a vital role in website designs. However, website designers give much effort to some realistic issues such as functionality and usability while the user's emotional need towards attractive websites are not paid enough attention, therefore, this study is important for developing and aesthetically attractive website.

The study is important for Information Technology (IT) professionals, especially website designers who are not generally interested in emotions since the quality of a website cannot solely be determined by the functionality. It examines the relationship between student's evaluation of universities websites and formal design attributes using Kansei Engineering, and how their emotions can be translated into measurable parameters.

It is crucial for academic websites as they are generally designed with more consideration on their functionality and whereas very little contemplations are given to the aesthetic need of the users which are mainly students.

The study carefully investigates the importance of transforming the user's (student's) emotional aspects to easily understandable numeric using multivariate statistical analyses that can help website designers and universities to understand that without satisfying the user's aesthetic needs their websites are incomplete even though they are functional and usable.

3.9. Limitation of the Study

This study has some limitations. One of the limitations is that during the evaluation, participants of the study did not interact with the websites; their evaluation was only based on visual design perception. For this reason, the result should only be interpreted in the context of visual impression.

Another limitation is that even though all students were active users of websites, most of them were not knowledgeable about website designs. But they all had the capability and experience to evaluate their impression towards the appearance of websites. Finally, we used non-probability sampling, particularly Convenience sampling technique and that is another limitation of this study.

4. STATISTICAL METHODS AND INTERPRETATIONS

4.1. Factor Analysis

Factor Analysis (FA) is a multivariate statistical technique that has a long-standing dispute throughout its history (Johnson & Wichern, 2007). Karl Pearson and Charles Spearman lied the foundation of modern factor analysis in the 20th century by measuring and testing human intelligence. After that Factor analysis became one the most widely used multivariate statistical techniques in many fields.

Factor analysis is used to minimize a large number of highly correlated variables to shrink it into a smaller number of latent variables called factors without losing much of the information. Based on the purpose and goal of the study, Factor analysis can be classified as Confirmatory Factor Analysis (CFA) and Exploratory factors analysis (EFA).

Confirmatory factor analysis is used to test a hypothesis that there is a relationship between observed variables and their latent construct. In this type of Factor analysis, a researcher decides the pattern of the relationship prior the study by using theory based on knowledge and then he/she tests that hypothesis statistically significant.

The researcher also proposes the number of factors that exist and which factor each variable will load before he/she can found any statistical results (Hair et al., 2007). Unlike CFA, in EFA, a researcher has no idea the factors that exist and as the name implies it is exploratory in nature, therefore, in our study we will use EFA.

Exploratory Factor analysis is widely used in Kansei Engineering (KE). In KE, we often collect a large number of variables known as Kansei Words but the question is, how these large set of variables can be grouped?. Factor analysis will help you to get the answer to this question.

Factor Analysis is a data reduction technique, which is used when there are a large number of correlated variables (Kansei Words) to summarize into a smaller number of unobservable variables called factors without losing much of the information. Kansei words, which have a common meaning, are grouped into similar groups and this reduces the number of required variables (Mamaghani et al., 2014). After that, a smaller number of variables (Kansei words) which contains most of the information will be synthesized to easily understand the structure of Kansei words hence it is easier to interpret a smaller number of uncorrelated Kansei words than a large set of variables correlated to each other.

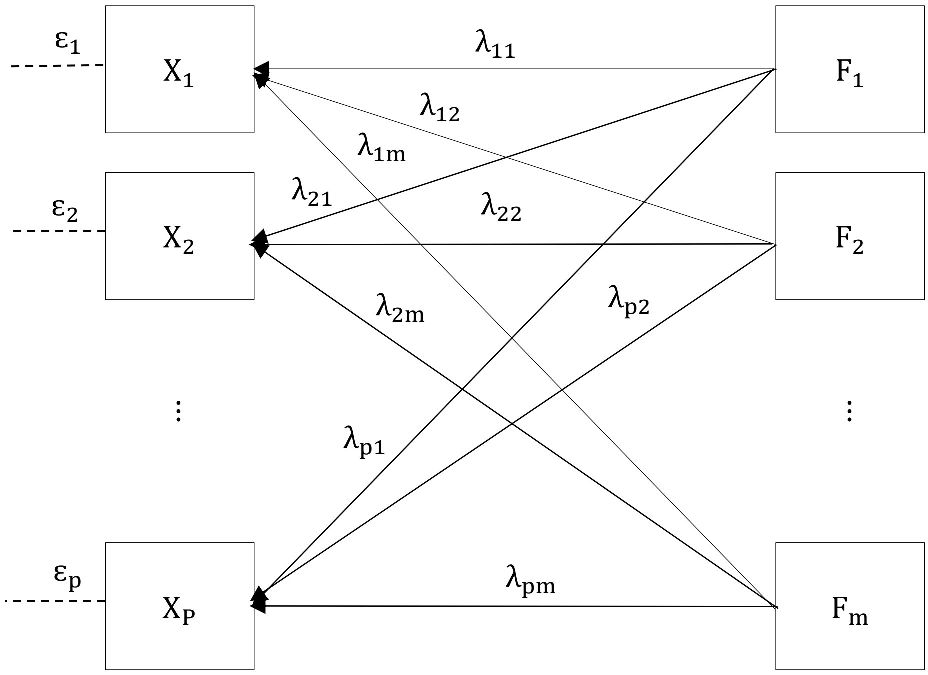

Figure 4.13. *Exploratory Factor Model*

The factor model look like that of multiple regression. It predicts the observable random variables X_i from unobserved common factors f_i. The variables μ_1 through μ_p can be considered as the intercept of multiple regression.

The Model is defined as:

$$\begin{aligned} X_{i1} &= \mu_1 + \lambda_{11}F_{i1} + \lambda_{12}F_{i2} + \cdots + \lambda_{1m}F_{im} + \varepsilon_{i1} \\ X_{i1} &= \mu_2 + \lambda_{21}F_{i1} + \lambda_{22}F_{i2} + \cdots + \lambda_{2m}F_{im} + \varepsilon_{i2} \\ &\vdots \\ X_{ip} &= \mu_p + \lambda_{p1}F_{i1} + \lambda_{p2}F_{i2} + \cdots + \lambda_{pm}F_{im} + \varepsilon_{ip} \end{aligned} \tag{4.1}$$

Therefore, as we see the above common Factor Model is similar to that of the multiple regression model, but to be more concisely we can put in a matrix form.

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}_{(px1)} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_3 \end{bmatrix}_{(px1)} + \begin{bmatrix} \lambda_{11} & \lambda_{12} & \dots & \lambda_{1m} \\ \lambda_{21} & \lambda_{22} & \dots & \lambda_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1p} & \lambda_{2p} & \dots & \lambda_{pm} \end{bmatrix}_{(pxm)} \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_m \end{bmatrix}_{(mx1)} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix}_{(px1)}$$

Where X_i is the response vector of person $i(i = 1, 2, \dots, n)$ containing variables $j = 1, 2, \dots, p$, μ is the mean vector, Λ is the matrix of factor loadings, F_i is the unobservable factors for person i, containing factor scores $k = 1, 2, \dots, m$ and finally, ε_i is the random error term to show that relationship between factors is not exact.

Based on the above matrix form, the variation of the data is controlled by m unobserved variables $f_1, f_2, \dots, f_m$ because the response variables $x_1, x_1, \dots, x_p$ can be predicted as the linear function of that unobserved variables.

The Matrix notation can be reduced:

$$\mathrm{X}_i = \mu + \Lambda \mathrm{F}_i + \varepsilon_i \tag{4.2}$$

Exploratory Factor analysis make assumptions that allows for estimation of all factor loadings for each requested factors. There are many unobservable variables in equation (4.2); therefore, direct verification of factor model by using $X_1, X_2, \dots, X_p$ is not possible. More assumptions about the random vectors F and ε, shows some covariance which can be checked.

We assume the unobservable factors $\mathrm{F_i}$ in (4.2) are independent of each other and of the error term, the expected value of the jth factor is zero. The variance of the unobservable factors $\mathrm{F_i}$ is one, and the covariance of the $\mathrm{F_i}$ is an identity matrix **I**. In addition, we assume that the error terms are independent of each other. Finally, we assume that the covariance of the error term and the factors is also zero.

F and ε are independent, so that

$$\mathrm{Cov}(\varepsilon, \mathrm{F}) = \mathrm{E}(\varepsilon \mathrm{F}^{\mathrm{T}}) = 0_{(pxm)}$$

$$\mathrm{E}(\mathrm{F}) = 0_{(mx1)}, \quad \mathrm{Cov}(\mathrm{F}) = \mathrm{E}(\mathrm{F}\mathrm{F}^{\mathrm{T}}) = \mathrm{I}_{(mxm)}$$

$$\mathrm{E}(\varepsilon) = 0_{(px1)}, \quad \mathrm{Cov}(\varepsilon) = \mathrm{E}(\varepsilon\varepsilon^{\mathrm{T}}) = \Psi_{(pxp)} \tag{4.3}$$

$$= \begin{bmatrix} \psi_1 & 0 & \cdots & 0 \\ 0 & \psi_2 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \psi_p \end{bmatrix}$$

If the Factor Model in (4.2) holds the assumptions mentioned in (4.3) is said to be Exploratory and Orthogonal factor model. The unobservable random vector F and ε satisfies the below mentioned conditions which are important for orthogonal and exploratory factor model.

F and ε are independent

$$\mathrm{E(F)=0} \quad \mathrm{Cov(F)=I}$$

$$E(\varepsilon) = 0 \quad cov(\varepsilon) = \psi$$

If the factor model satisfies the assumption in (4.3) mentioned earlier, the covariance matrix of the observed variables X can be decomposed as the factor-loading matrix multiplied by its transpose plus diagonal matrix of the specific variance (Johnson & Wichern, 2007) as shown below:

$$\Sigma = \Lambda\Lambda^{\mathrm{T}} + \psi \tag{4.4}$$

If we know the loading matrix Λ and the specific variance ψ that means we variance-covariance matrix Σ. Therefore,

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1m} \\ \lambda_{12} & \lambda_{22} & \ldots & \lambda_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1p} & \lambda_{2p} & \cdots & \lambda_{pm} \end{bmatrix}$$

Where λ's are loadings λ_{ij} = loadings of k^{th} factor on j^{th} X variables. $(i = 1, \ldots, p)(j = 1, \ldots, m)$.

Now, we have loading matrix; therefore, multiply its transpose.

$$\Lambda\Lambda^{\mathrm{T}} = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \ldots & \lambda_{1m} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{p1} & \lambda_{p2} & \cdots & \lambda_{pm} \end{bmatrix} \begin{bmatrix} \lambda_{11} & \lambda_{21} & \ldots & \lambda_{p1} \\ \lambda_{12} & \lambda_{22} & \cdots & \lambda_{p2} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1m} & \lambda_{2m} & \cdots & \lambda_{pm} \end{bmatrix}$$

$$= \begin{bmatrix} \sum_{\mathbf{k=1}}^{\mathbf{m}} \boldsymbol{\lambda}_{\mathbf{1k}}^{\mathbf{2}} & \sum_{k=1}^{m} \lambda_{1k}\lambda_{2k} & \ldots & \sum_{k=1}^{m} \lambda_{1k}\lambda_{pk} \\ \sum_{k=1}^{m} \lambda_{1k}\lambda_{2k} & \sum_{\mathbf{k=1}}^{\mathbf{m}} \boldsymbol{\lambda}_{\mathbf{2k}}^{\mathbf{2}} & \cdots & \sum_{k=1}^{m} \lambda_{2k}\lambda_{pk} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{k=1}^{m} \lambda_{1k}\lambda_{pk} & \sum_{k=1}^{m} \lambda_{2k}\lambda_{pk} & \cdots & \sum_{\mathbf{k=1}}^{\mathbf{m}} \boldsymbol{\lambda}_{\mathbf{pk}}^{\mathbf{2}} \end{bmatrix}$$

The off diagonal elements of this matrix is zero or very close to zero while the diagonal elements are the covariance components and related each of the variables.

$$\Lambda\Lambda^{T} + \psi = \begin{bmatrix} \sum_{k=1}^{m} \lambda_{1k}^{2} & & & \\ & \sum_{k=1}^{m} \lambda_{2k}^{2} & & \\ & & \ddots & \\ & & & \sum_{k=1}^{m} \lambda_{pk}^{2} \end{bmatrix} + \begin{bmatrix} \psi_{11} & 0 & \cdots & 0 \\ 0 & \psi_{22} & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \psi_{pp} \end{bmatrix}$$

$$= \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{12} & \sigma_{22} & \cdots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1p} & \sigma_{2p} & \cdots & \sigma_{pp} \end{bmatrix}$$

It is important to have a closer look at the diagonal elements of the matrix on both sides of the equality sign, which simply indicates that the first variance is the first loading matrix and its specific variance, the second variance is the second loading matrix and its specific variance and so on. In this matrix the off-diagonal element are always zero or very close to zero.

So that, mathematically we can write as following:

$$\sigma_{11} = \sum_{k=1}^{m} \lambda_{1k}^{2} + \psi_{11}$$

$$\sigma_{22} = \sum_{k=1}^{m} \lambda_{2k}^{2} + \psi_{22}$$

$$\vdots$$

$$\sigma_{jj} = \sum_{k=1}^{m} \lambda_{pk}^{2} + \psi_{jj}$$

Here, the total variability of $Var(X_i) = \sigma_{jj}$ is portioned into two different quantities, the first quantity $\sum_{k=1}^{m} \lambda_{pk}^{2} = h_i^2$ is called *Communality,* which represent the portion of the variability contributed by common factors. The other quantity ψ_{jj} is called *specific variance or unique variance;* it is the part of the variance of x_i that is not contributed by the common factors.

The communality can be:

$$h_i^2 = \lambda_{i1}^2 + \lambda_{i2}^2 + \cdots + \lambda_{im}^2 \tag{4.5}$$

and $$\sigma_{jj} = h_j^2 + \psi_{jj} \qquad j = 1, 2, \ldots, p$$

The common Factor Model also specifies that the factor loadings provide the covariance between the observable variables X_i and unobservable factors F_i, by using assumptions of the common and unique factors in (4.3).

$$\begin{aligned} \mathrm{Cov}(X, F) &= E\Big((X - \mu) - (F - E(F)^T\Big) \\ &= E\Big((X - \mu)F^T\Big) \\ &= E\Big((\Lambda F + \varepsilon)F^T\Big) \\ &= E(\Lambda F F^T) + E(\varepsilon F^T) \\ &= \Lambda E(FF^T) \\ \mathrm{Cov}(X, F) &= \Lambda \end{aligned} \tag{4.6}$$

4.1.2. EFA model estimation

In practical point of view, we do not know covariance matrix **Σ**, but we can estimate it by using sample covariance matrix **S** or sample correlation matrix **R** if the data we are dealing with is standardized data. We attempt therefore to estimate $\widehat{\boldsymbol{\Lambda}}$ and $\widehat{\boldsymbol{\psi}}$ just as $\widehat{\boldsymbol{\Lambda}}\widehat{\boldsymbol{\Lambda}}^{\boldsymbol{T}} + \widehat{\boldsymbol{\psi}}$ is very close to sample covariance matrix **S**.

In Exploratory Factor analysis, several different methods of estimating factor loadings **Λ** and specific factors ψ are used. Principal component method, principal factor method, maximum likelihood estimation are including some of the most popular methods of estimating Factor Model (Johnson & Wichern, 2007; Barbara & Linda, 2007) However, in this study we will use Principal Component estimation.

4.1.2.1. *Principal component analysis*

Principal component analysis is one of the most common used estimation of Factor analysis that is completely free from distribution. In this method, the sample covariance matrix S is used to estimate the unknown population covariance matrix Σ. When the off-diagonal elements of sample covariance matrix S are small or if the off diagonal of the sample correlation matrix R is literally zero, there are correlations among variables.

However, in this case, specific variance is the dominant. Otherwise, the factor model is interesting but the essential problem is estimating the factor loadings $\mathbf{\Lambda}$ and the specific variance ψ.

To estimate covariance matrix in equation (4.4) is difficult because the estimators of covariance matrix Σ, factor loading matrix $\mathbf{\Lambda}$, and the specific variance ψ is unknown, but we know the sample covariance matrix S.

In PCA method, the covariance matrix Σ is decomposed by its eigenvalue and eigenvector pairs (Q_j, e_j) with $Q_1 \geq Q_2 \geq \cdots \geq Q_j \geq 0$. This decomposition is known as the spectral decomposition and can be written:

$$\Sigma = \sum_{j=1}^{p} \mathrm{Q_j\, e_j e_j^T}$$

$$\Sigma = \mathrm{Q_1 e_1 e_1^T + Q_2 e_2 e_2^T + \cdots + Q_P e_p e_p^T}$$

$$= \left[\sqrt{\mathrm{Q_1}}\mathrm{e_1} \vdots \sqrt{\mathrm{Q_2}}\mathrm{e_2} \vdots \cdots \vdots \sqrt{\mathrm{Q_m}}\mathrm{e_m} \vdots \cdots \vdots \sqrt{\mathrm{Q_P}}\mathrm{e_p}\right] \begin{bmatrix} \sqrt{\mathrm{Q_1}}\mathrm{e_1^T} \\ \cdots \\ \sqrt{\mathrm{Q_2}}\mathrm{e_2^T} \\ \cdots \\ \vdots \\ \cdots \\ \sqrt{\mathrm{Q_m}}\mathrm{e_m^T} \\ \cdots \\ \vdots \\ \cdots \\ \sqrt{\mathrm{Q_p}}\mathrm{e_p^T} \end{bmatrix} \tag{4.7}$$

This is similar to the covariance structure $\mathbf{\Sigma}$ of factor analysis model having many factors like variables $(\mathrm{m = p})$ and specific variances $\psi_\mathrm{i} = 0$ and we assume that $\mathbf{\Sigma}$ is full rank. Therefore, we can write:

$$\Sigma_{(\mathrm{pxp})} = \Lambda_{(\mathrm{pxp})}\Lambda^{\mathrm{T}}_{(\mathrm{pxp})} + 0_{(\mathrm{pxp})} = \Lambda_{(\mathrm{pxp})}\Lambda^{\mathrm{T}}_{(\mathrm{pxp})} \tag{4.8}$$

The factor analysis representation in equation (4.8) is not useful because there many common factors as there variables and does not allow any variation in the specific factor.

We prefer model that illustrate the covariance in terms of few underlying common factors. When the last $p - m$ eigenvalues is small, it is to ignore the contribution of $\sqrt{Q_{m+1}}e_{m+1} \vdots \sqrt{Q_{m+2}}e_{m+2} \vdots \cdots \vdots \sqrt{Q_p}e_p$ and its transpose to covariance matrix Σ in equation (4.7) then we obtain:

$$\Sigma = \left[\sqrt{Q_1}e_1 \vdots \sqrt{Q_2}e_2 \vdots \cdots \vdots \sqrt{Q_m}e_m\right] \begin{bmatrix} \sqrt{Q}_1 e_1^{\mathrm{T}} \\ \cdots \\ \sqrt{Q}_2 e_2^{\mathrm{T}} \\ \cdots \\ \vdots \\ \cdots \\ \sqrt{Q}_m e_m^{\mathrm{T}} \end{bmatrix} = \mathbf{\Lambda\Lambda^T} \tag{4.9}$$

The approximate representation in (4.9) estimates the specific factors are not essentially important and can be neglected in factoring of covariance matrix $\mathbf{\Sigma}$. In case the specific factors are including in the model their variance can be treated to be the diagonal elements of $\mathbf{\Sigma} - \mathbf{\Lambda\Lambda^T}$. where $\mathbf{\Lambda\Lambda^T}$ is defined in equation (4.9).

Allowing specific factors, the approximation becomes

$$\widehat{\mathbf{\Sigma}} = \widehat{\mathbf{\Lambda}}\widehat{\mathbf{\Lambda}}^{\mathbf{T}} + \widehat{\boldsymbol{\psi}} = \left[\sqrt{\widehat{Q}_1}\hat{e}_1 \vdots \sqrt{\widehat{Q}_2}\hat{e}_2 \vdots \cdots \vdots \sqrt{\widehat{Q}_m}\hat{e}_m\right]$$

$$\begin{bmatrix} \sqrt{\widehat{Q}}_1 \hat{e}_1^{\mathrm{T}} \\ \cdots \\ \sqrt{\widehat{Q}}_2 \hat{e}_2^{\mathrm{T}} \\ \cdots \\ \vdots \\ \cdots \\ \sqrt{\widehat{Q}}_m \hat{e}_m^{\mathrm{T}} \end{bmatrix} + \begin{bmatrix} \psi_1 & 0 & \cdots & 0 \\ 0 & \psi_2 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \psi_p \end{bmatrix} \tag{4.10}$$

By using spectral decomposition of principal component analysis, we found that the estimate covariance matrix $\widehat{\mathbf{\Sigma}} = \mathbf{S}$ is the factor-loading matrix and its transpose added by the remaining portion that factor loading is not explaining. The factors can be:

$$\begin{aligned} \mathrm{F}_1 &= \sqrt{\widehat{\mathrm{Q}}_1}\ \hat{\mathrm{e}}_1 \\ \mathrm{F}_2 &= \sqrt{\widehat{\mathrm{Q}}_2}\ \hat{\mathrm{e}}_2 \\ &\vdots \\ \mathrm{F}_\mathrm{m} &= \sqrt{\widehat{\mathrm{Q}}_\mathrm{m}}\ \hat{\mathrm{e}}_\mathrm{m} \end{aligned} \tag{4.11}$$

The terms $\sqrt{\widehat{\mathrm{Q}}_1}, \sqrt{\widehat{\mathrm{Q}}_2}, \dots, \sqrt{\widehat{\mathrm{Q}}_\mathrm{m}}$ are eigenvalues, while $\hat{\mathrm{e}}_1,\ \hat{\mathrm{e}}_2, \dots, \hat{\mathrm{e}}_\mathrm{m}$ are eigenvectors of px1 matrix. Generally, we assume the population covariance matrix Σ is similar to the sample covariance matrix S and we want the difference between them to as small as possible.

Therefore,

$$S = \hat{\Lambda}\hat{\Lambda}^T + \hat{\psi} \tag{4.12}$$

However, that it is easy to find $\hat{\mathbf{\Lambda}}\hat{\mathbf{\Lambda}}^{\mathbf{T}}$and $\hat{\boldsymbol{\psi}}$ by simply manipulating equation (4.12).

4.1.3. Factor model adequacy test

Bartlett's Sphericity test was developed (Bartlett, 1951). It is used to check significance of factor analysis by comparing the observed correlation matrix to identity matrix. To measure the relationship between all variables, the determinant of the Correlation Matrix $|R|$ is calculated.

The hypothesis is that:

H_0: $|R| = 1$, When variables are highly correlated

H_A: $|R| = 0$, if there is no correlations between the variables. Here, the Bartlett's test statistic is to examine to what extent we differ from the null hypothesis.

$$\chi^2 = -\left[(n-1) - \frac{2p+5}{6}\right] \ln|R| \tag{4.13}$$

The null hypothesis H_0 follows a χ^2 distribution with *[p(p-1)/2]* degree of freedom. Where, p is the number of variables, n is the number of observations and R is the correlation matrix (Kaiser, 1970).

4.2. Partial Least Squares Regression

Partial Least Squares (PLS) regression is a popular multivariate statistical tool used to estimate the causal relationship between variables. It was developed by Hernan Ole Andreas Wold in 1975 (Mitsuo Nagamachi, 2011).

Partial Least Squares regression designed to challenge problems that arise in multiple regression analysis, when there are many correlated predictor variables or collinearities problems the Ordinary Least Squares (OLS) regression provides coefficients, which have high standard errors, and/or it fails.

PLS is the least restrictive method of the distinct types of multivariate extensions of multiple regression models. This allows it to be used as a remedy for those limitations and weaknesses. This multivariate statistical tool is applied where the problems exist such as medicines, economics, psychology, and most recently in Kansei engineering and where response variables are large compared to the number predictor variables.

İn Kansei Engineering studies, the PLS regression is utilized to spot the relations between Kansei words (Y) which are response variables and the predictor variables which are website designs (X) in our case (Lokman et al., 2008).

Partial Least Squares is also exploited to discover the impact of design categories in each Kansei words, the biggest positive values and biggest negative values for each design categories, and which sample influences what sort of Kansei (Lokman et al, 2009).

PLS regression was presented how a heuristic algorithm, based on algorithm Nonlinear Iterative Partial Least Squares (NIPALS) for calculation of eigenvectors, but quickly it was interpreted as a statistical structure (Frank, I.E., & Friedman, J.H, 1993). The PLS method merges or combines and generalizes characteristics Principal Component Analysis and Multiple Regression Analysis.

PLS regression is applied to KE. The reason is to create a linear model:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{E} \tag{4.14}$$

where Y_{nxm} response matrix. The rows correspond to n specimens and columns correspond to p Kansei words (average) in each specimen, and X_{pxp} matrix where p columns correspond to p dummy variables of each category of specimens, β_{pxm} regression coefficient matrix, and **E** is an error term and has the same dimension as that of **Y**. Normally, the variables in Y and X are centered by subtracting their means and scaled by dividing their standard deviation before numerical treatment (Geladi, P., and Kowlaski B. , 1986).

The regression coefficient matrix β can be found:

$$\beta = (X^T X)^{-1} X^T Y \tag{4.15}$$

Usually, $X^T X$ is singular, either because there are highly correlated predictor variables or because the number of columns in X are larger than the number of rows. However, PLS regression avoids this problem by decomposing X and Y matrices into bilinear terms plus error matrices to build a linear model (Qin, 1998).

$$X = TP^T + E_k = t_1 p_1^T + t_2 p_2^T + \cdots + t_k p_k^T + E_k \tag{4.16}$$

Where t_k are *latent variables*, p_k are *loadings*, E_k are error matrix, and K is the number of components Partial least square. On the other hand, the response variables Y can be decomposed as follows:

$$\begin{aligned} Y &= TQ^T + f_k \\ Y &= t_1 q_1^T + t_2 q_2^T + \cdots + t_k q_k^T + f_k \end{aligned} \tag{4.17}$$

Similarly, t_k are *latent variable* vectors, q_k are corresponding *loading* vectors, f_k are error matrices. Therefore, we clearly see that the relationship between Y and X is connected by the latent variables T. However, one important point is, how to calculate the latent variables T.

PLS regression calculates latent variables (also known as factor score matrix) $T = WQ$ for proper matrix of weights W which represents the structure of the covariance between predictor variables and response variables, moreover it contemplates the regression linear model $Y = TQ + E$, here Q is the loading vectors (coefficients) for T, while **E** is an error term. When the regression loadings **Q** are figured out the $Y = TQ + E$ is similar to multiple linear regression model $Y = X\beta + E$, where coefficients $\beta = WQ$ can be applied like a regression model.

The estimation procedure of PLS regression is made by a sequences of steps in algorithm form. There are two various forms of estimation which are univariate PLS regression (PLS1) and multivariate PLS regression (PLS2).

4.3. Results and Interpretations

Before running multivariate statistical analyses, we will examine the semantic differential chart of the average numbers of Kansei responses for each of the 9 sample websites and the descriptive statistics of the respondents.

Semantic Differential (SD) method developed by (Carroll, 2016) is used to visually explore association between student's evaluation of website samples and Kansei words. Figure 4.14 portrays good information about student's position on a scale of two bipolar words and the respondent's average score for each of the 9 websites. The data is well distributed below and above 3 that is the neutral response value. We can visually see that some websites (from 1 to 4) are above three and others are below this value.

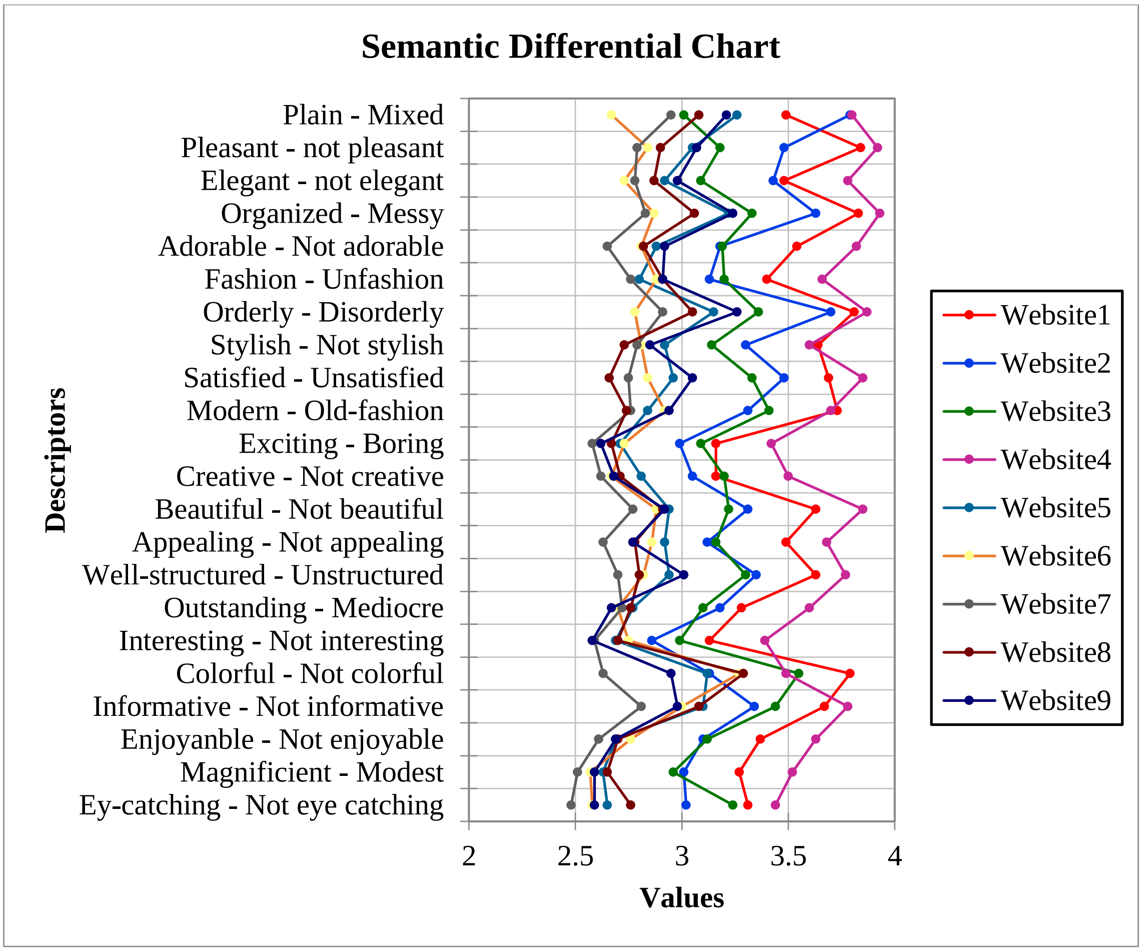

Figure 4.14. *Kansei Words Vs Sample Websites*

The data we used are obtained this survey was collected students from seven different Turkey universities, which lasts one month. The following tables illustrates respondent's gender distribution of the survey and student's class status and their living places respectively.

Table 4.3. *Respondent's Gender*

Gender	Number of respondents	Percentage %
Female	84	48.8
Male	88	51.2
Total	172	100.0

Tables 4.3 indicates that 172 respondents participated this survey. Both male and female students have an approximately equal proportion of participation in the survey. 48.8% of respondents were female students, while the remaining 51.2% of the respondents were male students.

Table 4.4. *Respondent's Class Status*

Class status	Number of respondents	Percentage %
Freshman	21	12.2
Junior	49	28.5
Master	7	4.1
PHD	4	2.3
Senior	49	28.5
Sophomore	42	24.4
Total	172	100.0

The above table 4.4 shows that 28.5% of the respondents were junior and senior students, so and they have the largest proportion participation. 24.4% of the respondents were sophomore (2nd year) students. However, Ph.D. and Master students were the least participants 2.3% and 4.1% percent respectively.

Table 4.5. *Respondent's Living Area*

Living place	Number of respondents	Percentage %
Appartment	8	4.7
Dormitory	77	44.8
Stay house alone	18	10.5
Stay House with friends	25	14.5
Stay with family	44	25.6
Total	172	100.0

According to table 4.5, around half (44.8%) of the respondents live in a dormitory and 25.6% live in with their families, but 14.5% live in a rented home with their friends and only 10.5% live a rented house alone.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericity

Before we do any factor extractions, to confirm whether our data is suitable to run exploratory factor analysis, there are several tests used to assess the suitability of the data for exploratory factors analysis. Some of the most popular tests include Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Hair et al., 2007), and Bartlett's test of Sphericity. The KMO value ranges from 0 to 1, therefore, a KMO value of 0.5 is considered to be applicable for factor analysis (Hair et al., 2007). On the other hand, Bartlett's test of Sphericity should be significant at a certain threshold limit of alpha ($p<0.05$).

Table 4.6. *KMO and Bartlett's Test*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.953
Bartlett's Test of Sphericity	Approx. Chi-Square	4276.555
	df	231
	Sig.	.000

In our case, table 4.6. displays that, the overall value of KMO measure of sampling adequacy is 0.95, which is very close to 1 and greater than 0.5 as mentioned earlier and Bartlett's test of Sphericity is significant (χ^2 (231) = 4276.6, $p < .05$), therefore it is appropriate and acceptable to run factor analysis.

After identifying that, the data is suitable for factor analysis; the next step is to find the structure of Kansei words by running factor analysis. In here, our purpose is to find a smaller number of factors that contributes significantly more weight. Several different options are considered when determining the number of factor to be extracted.

Table 4.7. *Factor Contribution*

	F1	F2	F3	F4	F5	F6	F7	F8
Eigenvalue	20.163	1.064	0.336	0.183	0.128	0.059	0.051	0.015
Variability (%)	91.648	4.839	1.530	0.834	0.581	0.269	0.230	0.070
Cumulative %	91.648	96.487	98.016	98.850	99.431	99.700	99.930	100.000

In table 4.7, it is clear that based on varimax rotation with Kaiser Normalisation; the eight factors have a cumulative contribution of 100%. However, using Kaiser's criteria of eigenvalues greater than or equal to 1, the first two factors have eigenvalues greater than 1.

Factor 1 has an eigenvalue of 20.163, therefore, it explains 91.65% of the total variability of the data, which represents the majority of the main factor contribution and have the dominant effect of Kansei words.

Factors 2 has an eigenvalue of 1.064, which is greater than 1, it also explains 4.84% of the data and has the second largest contribution, that means, the first two factors only explain 96.49% of total variability of the data. Meanwhile, the remaining factors have smaller contribution; therefore, we would use the Kansei words that loads higher in factor one and those load higher in factor two.

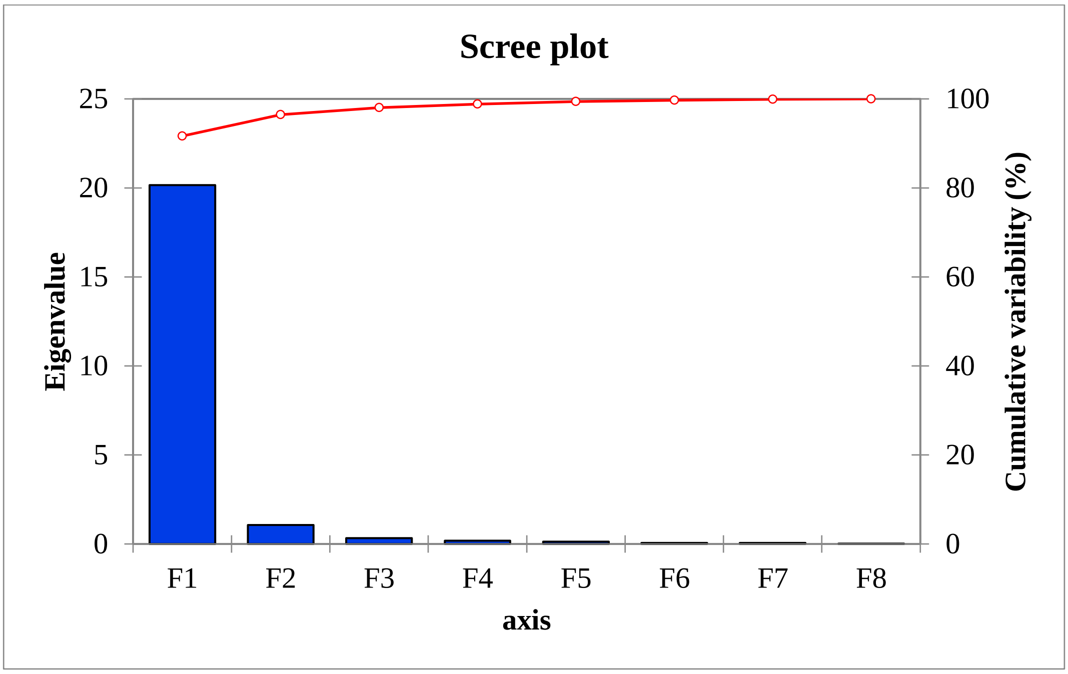

Figure 4.15. *Scree Plot of the Factor Analysis*

Scree plot in another method of extracting the number of factors, which was developed by Cattell (1966). Scree plot is used to visually display which factors explain most of the variablity of data instead of using cumulative contribution in Table 4.7. It shows eigenvalues against each of the eight factors arranging in descending order.

In this case, it is evident that there is a clear change in the graph after factor two, that means only first two factors explain most of the variability in the data because the eigenvalues of the first two factors are greater than one. While the remaining factors explain a very small proportion of the total variability, therefore, they can be considered as unimportant. Generally, scree plot technique and cumulative contribution table display same results.

Table 4.8. *Factor Loading after Varimax Rotation*

	F1	F2
Plain - Mixed	0.155	**0.967**
Pleasant - not pleasant	0.601	**0.783**
Elegant - not elegant	0.532	**0.843**
Organized - Messy	0.548	**0.817**
Adorable - Not adorable	**0.733**	0.667
Fashion - Unfashion	**0.777**	0.602
Orderly - Disorderly	0.485	**0.855**
Stylish - Not stylish	0.661	**0.717**
Satisfied - Unsatisfied	0.629	**0.750**
Modern - Old-fashion	**0.773**	0.591
Exciting - Boring	**0.811**	0.563
Creative - Not creative	**0.759**	0.599
Beautiful - Not beautiful	**0.718**	0.690
Appealing - Not appealing	**0.789**	0.600
Well-structured - Unstructured	0.691	**0.713**
Outstanding - Mediocre	**0.693**	0.691
Interesting - Not interesting	**0.844**	0.499
Colorful - Not colorful	**0.917**	0.104
Informative - Not informative	**0.810**	0.576
Enjoyanble - Not enjoyable	**0.777**	0.618
Magnificient - Modest	**0.730**	0.676
Ey-catching - Not eye catching	**0.822**	0.531

Rotated factor matrix indicates the correlation between the variables (Kansei Words) and the factors (F1 and F2). The Factor columns represent the rotated factors that have been extracted out of the total factor. In factor loading after varimax rotation table, each variable loads highly in one factor and loads less towards the other factors.

Table 4.8 displays that, the sample website Kansei are structured two factors that are the loadings of Kansei words are in factor 1 and factor 2. From the Table 4.8, we can identify that Kansei words such as “Colorful”, “interesting”, “eye-catching”, “exciting”, “informative”, etc. load highly in factor 1, therefore, they can be grouped as “aesthetic” or “visual attraction” factor.

On the other side, Kansei words like “plain”, “orderly”, “elegant”, “organized” etc. load highly in factor 2, so they can be grouped as “personality”. These are the highest loading Kansei Words in each of their factors.

Based on the results in table 4.8, the website samples are formed two factors, namely, “aesthetic” or “visual attraction” and “personality. These two factors explain 96.49% of the total variability in the data.

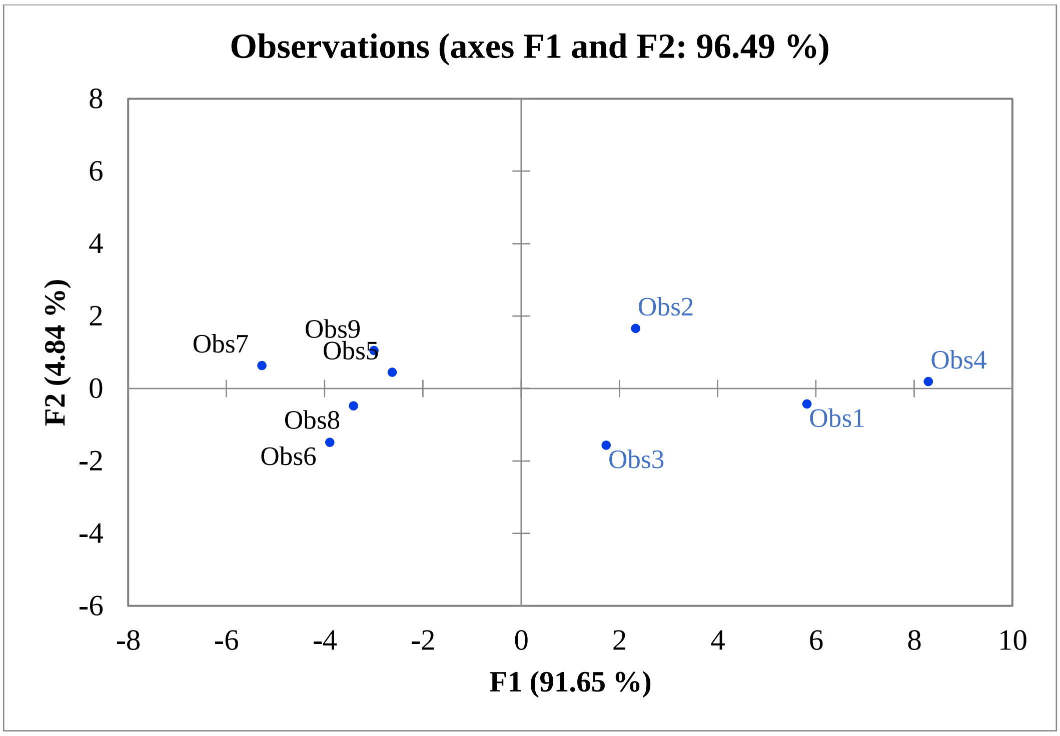

Figure 4.16. *PC score F1 and F2 Results of the Participants*

Figure 4.16 (PC score) shows the relationship between student’s Kansei and the nine websites. We can see that the Websites are separate in an order of preference, from Obs1 to Obs4 (overall highest ratings, on the right) to Obs7 (lowest ratings, on the left).

Website 4 has the highest overall ratings of all participants and the second highest rating is website 1 followed by websites 1 and 2. However, website 7 on the left corner has the lowest ratings of all participants followed by the other websites.

Finally, we can conclude that the first four websites have a strong positive impact on students Kansei (feeling) and the last five websites have a strong negative influence in students Kansei (feeling).

To further examine the relationship between Kansei words that have highest loadings in Table 4.8 and the detailed design of items and categories mentioned in table 3.1, we would be performing another statistical method called Partial Least Squares (PLS).

To examine the relationship between Kansei Words and items/categories of websites we picked Kansei Words that have a loading value of 0.80 and above in each factor. İn factor 1 we selected Kansei Words like Colorful (0.917), Interesting (0.844), Eye-catching (0.822) and Informative (0.810) and in factor 2 we selected Plain (0.967), Orderly (0.855), Elegant (0.843) and Organized (0.817). For simplicity purpose finally we picked the highest three loadings in each factor.

These Kansei words were the dependent variables and the independent variables were the categories (see Table 3.1) such as header color, the location of the Logo etc. The category values were used as dummy variables such as either 1 or 0. For examples, as Table 4.9 shows if a website had a logo on the left, its value is 1 and websites which did not have this type of category took a value of 0 and so on.

Table 4.9. *Sample of the Categories Identified from Websites*

Items	Header background color					Location of the Logo			
Websites/ Categories	White	Dark blue	Orange	Blue	Grey	Left	Right	Center	…
Website 1	1	0	0	0	0	1	0	0	…
Website 2	0	1	0	0	0	1	0	0	…
Website 3	0	0	1	0	0	1	0	0	…
Website 4	1	0	0	0	0	1	0	0	…
Website 5	0	0	0	1	0	0	1	0	…
Website 6	1	0	0	0	0	1	0	0	…
Website 7	0	1	0	0	0	1	0	0	…
Website 8	0	0	0	1	0	1	0	1	…
Website 9	0	0	0	0	1	0	1	0	…

For PLS regression, we used 41 categories from 14 different items (see Table 3.1) as predictor variables. However, the following results are only partial results.

The line loading plot figure shows visually which categories have a positive influence on student's Kansei towards website and which have negative impacts. It is a way of observing visually which website categories have the highest positive influence on student's feeling and which website categories (predictor variables) have the strongest negative impact on student's feeling.

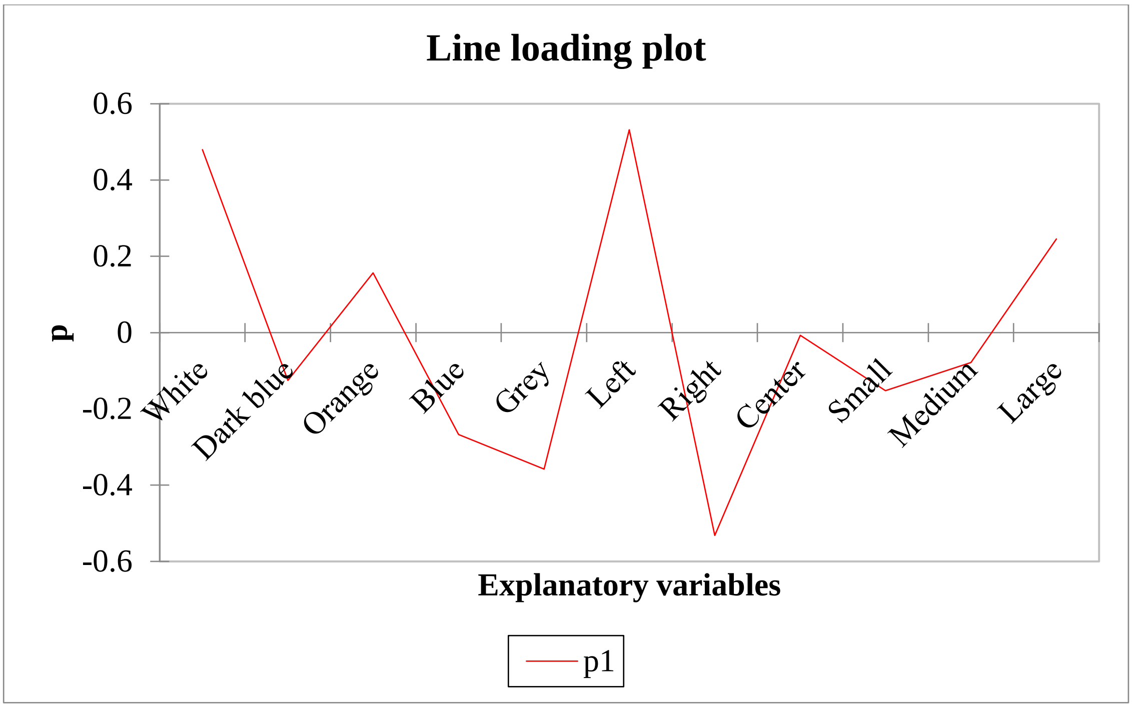

Figure 4.17. *Line loading plot for predictors*

We can see that colors such as White and orange have positive influence, the location area on the left also has a positive influence and finally, the size such as large has a positive effect. However, the other categories have a negative influence on student's Kansei. For further understanding, the following Table 4.10 implies the relationship between response variables (Kansei Words) and predictor variables (categories of websites).

Table 4.10. *Partial PLS regression results*

Items/categories		Colorful	Interesting	Eye-catching	Plain	Orderly	Elegant
	Intercepts	3.281	2.871	2.923	3.253	3.340	3.132
Header color	**White**	**0.059**	**0.030**	**0.044**	**0.004**	**0.031**	**0.025**
	Dark blue	-0.038	-0.020	-0.029	-0.003	-0.020	-0.016
	Orange	0.037	0.019	0.028	0.003	0.020	0.015
	Blue	-0.032	-0.016	-0.024	-0.002	-0.017	-0.013
	Grey	-0.047	-0.024	-0.035	-0.003	-0.025	-0.020
Location of the logo	**Left**	**0.046**	**0.024**	**0.034**	**0.003**	**0.024**	**0.019**
	Right	-0.046	-0.024	-0.034	-0.003	-0.024	-0.019
	Center	-0.023	-0.012	-0.017	-0.002	-0.012	-0.009
Title font size	Small	-0.006	-0.003	-0.004	0.000	-0.003	-0.002
	Medium	-0.020	-0.010	-0.015	-0.001	-0.010	-0.008
	Large	**0.034**	**0.017**	**0.025**	**0.002**	**0.018**	**0.014**

The PLS regression results in Table 4.10 indicates how the selected items/categories such as (Header color, the location of the Logo, and the title font size) influence student's responses on each of the six Kansei words. Categories with higher score values in each item have a strong positive influence on student's Kansei and those with negative score values has a negative effect.

Table 4.10, shows the first three items on the websites and each item has different categories. For example, the header color item, the white and orange colors have a strong positive impact on student's Kansei (feeling) towards websites. However, white color has the strongest positive effect, therefore, for this item; we selected white color when talking about header color of our sample websites. In addition to that, blue, grey, and dark blue colors have a strong negative influence on student's Kansei towards websites.

Coming to the second item (location of the logo) of the data analysis in Table 4.10 we can see that logo on the left side has the strongest influence on student's Kansei for the website, meanwhile, logo on the right side and centre have a negative impression on student's feeling. Considering the third item, which is the size of the text of the title, in Table 4.10, it is clear that both small and medium title font have a negative impact on student's perceptions towards website but large font has a positive effect on student's Kansei.

From the results in Table 4.10, for each item, the strongest positive category is chosen. Nevertheless, if two or more categories have the very close values their mean and variance of the parameters are calculated regarding the Kansei words, and the category with the highest mean value is preferred to choose. If there are categories with similar mean values the category that has smaller variance are determined to select.

The purpose of calculating mean values and variances is because the category which has a higher mean value has a very high positive impact on student's Kansei towards websites and the lower variance implies the influence on Kansei words are balanced. Based on the statistical results from Table 4.10, the category "white" was picked for the header color of the website, the category "left" was selected for the location of the logo and finally, the category "large" was preferred to be chosen for title font size. We made further analysis in each category and results are summarized the following results.

Table 4.11. *Results of the Other Categories*

Header size	Small
Footer size	Large
Footer color	Yellow
Top menu existence	Yes
Main body background color	White
Main body text font color	Blue, White and Green
Number of pictures	11 and more
Number of small pictures	6 and more
Number of large pictures	2 and more
Number of medium pictures	5 and more
Video button existence	No

These are the results of the statistical analyses, but a website with bigger score does not necessarily indicate all of its categories were designed in a proper style and accurately designed, however, the purpose and philosophy of the university, designers creativity skills are also considered to be important factors when designing visibly attractive university website.

5. FINDINGS AND DISCUSSIONS, CONCLUSION, AND RECOMMENDATIONS

5.1. Findings and Discussions

According to 4.3, 4.4, and 4.5 Tables, 84% of the respondents were female and 88% were male. In addition, more than half of the respondents (57%) were sophomore and junior (28.5% and 28.5%) respectively, were a junior student, besides that almost half (44.5%) of them were staying dormitory during the data collection. Table 4.6 shows that the overall value of the KMO measure of sampling adequacy is 0.95, and Bartlett's test of Sphericity is significant (χ^2 (231) = 4276.6, $p < 0.05$). This is a good sign that the data is appropriate to run the factor analysis.

Both SD char and PC score F1 and F2 Results of the Participants displayed that highest rating websites are included website 1, website 2, website 3, and website 4, meanwhile website 7 has the lowest rating website followed by website 6, website 8, website 9, and website 5 respectively. That means that the highest rating websites are the most attractive in term of student's feeling and the lowest rating are least attractive websites.

The scree plot figure and the factor contribution table also implied that the first two factors explain 96.49% of the data and other six factors explain the rest. Factor 1 explained 91.65% of the data so that the variables of this factor are grouped as "aesthetic factor". Factor 2 explains 4.84% of the data and the variables in this factor are grouped as personality factor.

To investigate linear relationship between Kansei words in Factor 1 and Factor 2 and categories of each website we performed PLS regression and found some categories have a positive impact on student's feeling and some categories have a negative influence. The Partial PLS regression result table indicates that both white and orange header colors have a strong positive effect on student's feeling. Similarly, PLS results demonstrate that logo on the left side and large font in terms of the title are including some of the categories that have strong positive correlation on student's feeling (Kansei).

5.2. Conclusion

The study begins with the collection of 9 sample websites based on their limited physical appearances and 22 pairs of Kansei words related to the visual design of the sample websites was collected. To evaluate student's Kansei, the study proposes a 5-point semantic differential scale, and finally, Kansei words and the sample websites were put together side-by-side on one page. The target population of the study was Turkish students studying at universities in Turkey, therefore, 172 students from seven Turkey universities, between the ages of 18 to 37 years old participated in the study. Male (88%) and female (84%) students have an approximately equal proportion to the participation in the study.

To investigate student's Kansei towards website of the sample universities and explore categories of websites that highly influence on student's feelings we calculated Factor analysis and Partial Least Squares regression. Factor analysis was performed to determine the number of factors, the structure of the Kansei words, and the relation between student's Kansei responses and the sample website. The FA displayed that the KWs are structured two factors. The first factor explains 91.65% of the data and has a dominant effect. The second factor explain 4.84% of the data that means the first two factors explain 96.5% of the total variability of the data.

Factor analysis reveals the first four websites have biggest overall ratings, therefore, they have a strong positive impact on student's Kansei, while the last five websites (from a Website 5 to Website 9) have a negative influence on student's Kansei as they have lower ratings.

For further information, we performed PLS regression to inspect the relationship between Kansei words and website items/categories and to interpret student's Kansei responses to website design. Some of the categories that this study recommended are included, white header color, logo on the left side of the website, and small font title have a positive impact on student's perceptions towards the website.

The study also displayed categories that have a negative influence. The results proved that statistics, particularly FA and PLS regression, played a key role in website design to approach the student's need.

5.3. Recommendations

The study recommends the Information Technology (IT) professionals, particularly web designers, researcher, and universities, to carefully choose webpage categories before designing it. Doing this will support them to grasp the user's (students) feeling and design not only functional and usable but an aesthetically attractive website that meets expectations of the users.

According to the statistical outcome of the study, web designers and universities should select a white color as a header background, the logo should be on the left side, and university title font must be large font not small and medium when designing an academic website. To design a visibly attractive website that elicited student's Kansei, the header size of the website should be small and the footer size must be large. Some of the other major recommendations of the study are included.

- Footer color should be yellow
- Web page must have a top menu button
- Main body background color of the web page should be white
- The main font color must be blue, white and green
- There must 11 and more pictures on the website including small, medium and large pictures. 6 and more small, 2 and more large, and 5 and more small, large and medium pictures respectively.
- There should not be a video button on the website

Compared to these results to others, which are relevant to website design in KE application, Erdoğmuş studied website design using FA and Logistic Regression with KE. He found that comprehensive, dynamic, aesthetic, user-friendly, reliable, and well structured are the KWs that highly influenced emotions (Erdoğmuş et al., 2011). Erdoğmuş and his friends also recommended that website should have left menu and the menu color should be black. On the other hand (Song et al., 2012) found KWs like dynamic, exciting, bright, modern, beautiful, enjoyable, and well-structured highly influenced emotions. Song and his friends also recommended that an emotional website should have medium header size, dark red header background color, medium title font size, and large footer size.

These results are based on statistical analyses. However, even though they are statistically significant it is irrational to have a mixture of these categories. Practically it is impossible to clearly see blue, white and green fonts with white body background color.

Furthermore, a website with too many pictures may appear to be undesirable to some people. For all these details, the final design would be a combination of outcome from Factor Analysis and Partial Least Squares regression and other considerations including creativity and experiences of the web designer.

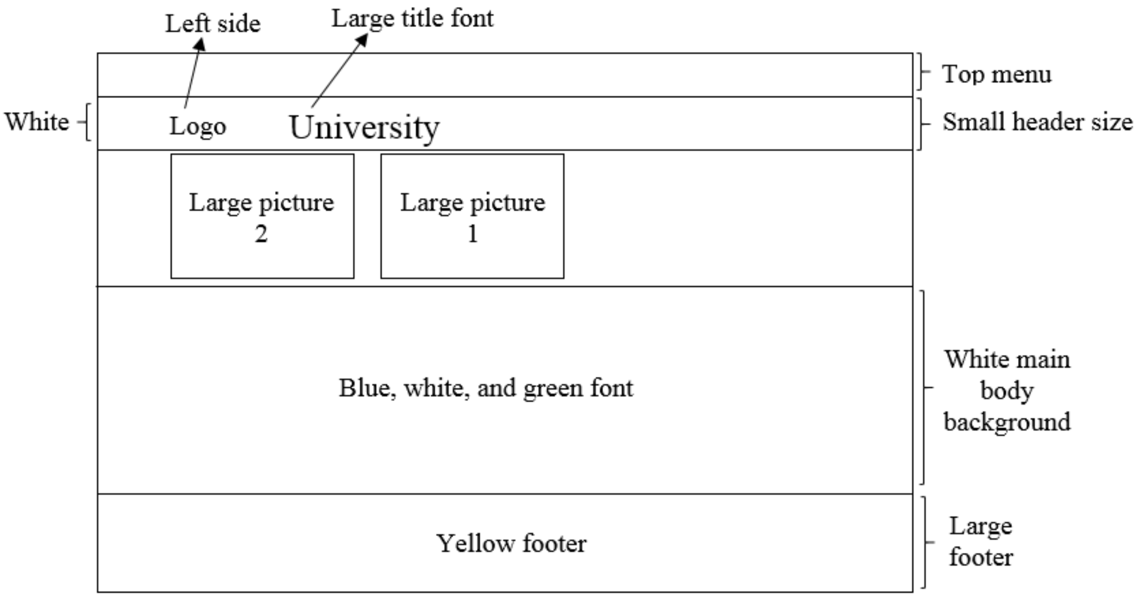

Figure 5.18. *Proposed Web Design*

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APPENDIX

SURVEY ABOUT USER’S OPINION TOWARDS WEBSITE DESIGNS

This survey is all about user’s opinion towards universities website designs. This questionnaire was prepared within the scope of Master's thesis. The data obtained from this questionnaire will not be used anywhere else. Please answer the questions correctly and sincerely. We aim at this study to see how it looks like organizing a similar website. Give your answers in the form of (X). THANK YOU for responding to the survey.

Demografik bilgiler / Demographic Information:

1) Cinsiyetiniz / Your gender

   ◯ Erkek / Male ◯ Kadın / Female

2) Yaşınız/ your age___________

3) Kaçıncı sınıfta okuyorsunuz / which of the following class status best describes your education year?

   ◯ Brinci yil/Freshman ◯ikinci yil/Sophomore ◯ Üçüncü yıl/Junior ◯Dördüncü/Senior ◯ Yuksek lisans/Master ◯Doktora/Ph.D

4) Okul yılı süresince nerede kalıyorsunuz / Where do you stay during your education period?

   ◯ Yurtda / Dormitory
   ◯ Evde tek başına / Stay house alone
   ◯ Evde arkadaşlarla / Stay home with friends
   ◯ Aileyle / stay with family
   ◯ Apartta / apartment

5) Öğrenim gördüğünüz üniversite / which university do you study___________________________

Lütfen, aşağıdaki web sitelerine ilişkin görüşlerinizi belirtiniz / please evaluate the visual design of the below websites.

E-Posta: saedja@anadolu.edu.tr

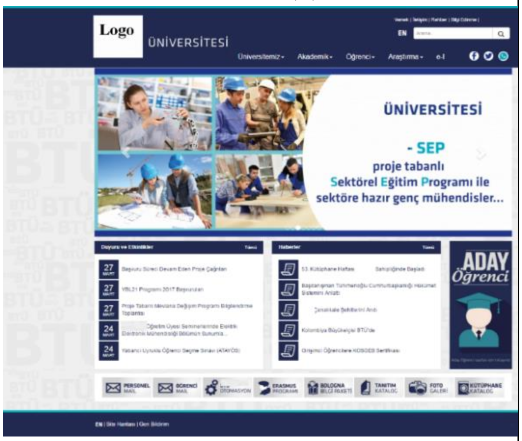
Domain (1)

How this website seems to you?

…………Very good … Not good…………..

	5 4 3 2 1	
Palin	☐ ☐ ☐ ☐ ☐	Mixed
Pleasant	☐ ☐ ☐ ☐ ☐	Not pleasant
Elegant	☐ ☐ ☐ ☐ ☐	Not elegant
Organized	☐ ☐ ☐ ☐ ☐	Messy
Adorable	☐ ☐ ☐ ☐ ☐	Not adorable
Fashion	☐ ☐ ☐ ☐ ☐	Unfashion
Orderly	☐ ☐ ☐ ☐ ☐	Disorderly
Stylish	☐ ☐ ☐ ☐ ☐	Not stylish
Satisfied	☐ ☐ ☐ ☐ ☐	Unsatisfied
Modern	☐ ☐ ☐ ☐ ☐	Old-fashion
Exciting	☐ ☐ ☐ ☐ ☐	Boring
Creative	☐ ☐ ☐ ☐ ☐	Not creative
Beautiful	☐ ☐ ☐ ☐ ☐	Not beautiful
Appealing	☐ ☐ ☐ ☐ ☐	Not appealing
Well-structured	☐ ☐ ☐ ☐ ☐	Unstructured
Outstanding	☐ ☐ ☐ ☐ ☐	Mediocre
Interesting	☐ ☐ ☐ ☐ ☐	Not interesting
Colorful	☐ ☐ ☐ ☐ ☐	Not colorful
Informative	☐ ☐ ☐ ☐ ☐	Not Informative
Enjoyable	☐ ☐ ☐ ☐ ☐	Not enjoyable
Magnificient	☐ ☐ ☐ ☐ ☐	Modest
Eye-catching	☐ ☐ ☐ ☐ ☐	Not eye-catching

Domain (2)

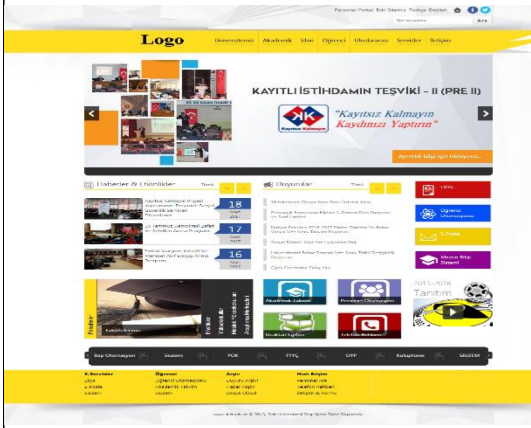


How this website seems to you?

…………Very good … Not good…………..

	5	4	3	2	1	
Palin	☐	☐	☐	☐	☐	Mixed
Pleasant	☐	☐	☐	☐	☐	Not pleasant
Elegant	☐	☐	☐	☐	☐	Not elegant
Organized	☐	☐	☐	☐	☐	Messy
Adorable	☐	☐	☐	☐	☐	Not adorable
Fashion	☐	☐	☐	☐	☐	Unfashion
Orderly	☐	☐	☐	☐	☐	Disorderly
Stylish	☐	☐	☐	☐	☐	Not stylish
Satisfied	☐	☐	☐	☐	☐	Unsatisfied
Modern	☐	☐	☐	☐	☐	Old-fashion
Exciting	☐	☐	☐	☐	☐	Boring
Creative	☐	☐	☐	☐	☐	Not creative
Beautiful	☐	☐	☐	☐	☐	Not beautiful
Appealing	☐	☐	☐	☐	☐	Not appealing
Well-structured	☐	☐	☐	☐	☐	Unstructured
Outstanding	☐	☐	☐	☐	☐	Mediocre
Interesting	☐	☐	☐	☐	☐	Not interesting
Colorful	☐	☐	☐	☐	☐	Not colorful
Informative	☐	☐	☐	☐	☐	Not Informative
Enjoyable	☐	☐	☐	☐	☐	Not enjoyable
Magnificient	☐	☐	☐	☐	☐	Modest
Eye-catching	☐	☐	☐	☐	☐	Not eye-catching

Domain (3)



How this website seems to you?

…………Very good … Not good…………..

	5	4	3	2	1	
Palin	☐	☐	☐	☐	☐	Mixed
Pleasant	☐	☐	☐	☐	☐	Not pleasant
Elegant	☐	☐	☐	☐	☐	Not elegant
Organized	☐	☐	☐	☐	☐	Messy
Adorable	☐	☐	☐	☐	☐	Not adorable
Fashion	☐	☐	☐	☐	☐	Unfashion
Orderly	☐	☐	☐	☐	☐	Disorderly
Stylish	☐	☐	☐	☐	☐	Not stylish
Satisfied	☐	☐	☐	☐	☐	Unsatisfied
Modern	☐	☐	☐	☐	☐	Old-fashion
Exciting	☐	☐	☐	☐	☐	Boring
Creative	☐	☐	☐	☐	☐	Not creative
Beautiful	☐	☐	☐	☐	☐	Not beautiful
Appealing	☐	☐	☐	☐	☐	Not appealing
Well-structured	☐	☐	☐	☐	☐	Unstructured
Outstanding	☐	☐	☐	☐	☐	Mediocre
Interesting	☐	☐	☐	☐	☐	Not interesting
Colorful	☐	☐	☐	☐	☐	Not colorful
Informative	☐	☐	☐	☐	☐	Not Informative
Enjoyable	☐	☐	☐	☐	☐	Not enjoyable
Magnificient	☐	☐	☐	☐	☐	Modest
Eye-catching	☐	☐	☐	☐	☐	Not eye-catching

Domain (4)

How this website seems to you?

…………Very good … Not good…………..

	5	4	3	2	1	
Palin	☐	☐	☐	☐	☐	Mixed
Pleasant	☐	☐	☐	☐	☐	Not pleasant
Elegant	☐	☐	☐	☐	☐	Not elegant
Organized	☐	☐	☐	☐	☐	Messy
Adorable	☐	☐	☐	☐	☐	Not adorable
Fashion	☐	☐	☐	☐	☐	Unfashion
Orderly	☐	☐	☐	☐	☐	Disorderly
Stylish	☐	☐	☐	☐	☐	Not stylish
Satisfied	☐	☐	☐	☐	☐	Unsatisfied
Modern	☐	☐	☐	☐	☐	Old-fashion
Exciting	☐	☐	☐	☐	☐	Boring
Creative	☐	☐	☐	☐	☐	Not creative
Beautiful	☐	☐	☐	☐	☐	Not beautiful
Appealing	☐	☐	☐	☐	☐	Not appealing
Well-structured	☐	☐	☐	☐	☐	Unstructured
Outstanding	☐	☐	☐	☐	☐	Mediocre
Interesting	☐	☐	☐	☐	☐	Not interesting
Colorful	☐	☐	☐	☐	☐	Not colorful
Informative	☐	☐	☐	☐	☐	Not Informative
Enjoyable	☐	☐	☐	☐	☐	Not enjoyable
Magnificient	☐	☐	☐	☐	☐	Modest
Eye-catching	☐	☐	☐	☐	☐	Not eye-catching

Domain (5)

How this website seems to you?

…………Very good … Not good…………..

	5	4	3	2	1	
Palin	☐	☐	☐	☐	☐	Mixed
Pleasant	☐	☐	☐	☐	☐	Not pleasant
Elegant	☐	☐	☐	☐	☐	Not elegant
Organized	☐	☐	☐	☐	☐	Messy
Adorable	☐	☐	☐	☐	☐	Not adorable
Fashion	☐	☐	☐	☐	☐	Unfashion
Orderly	☐	☐	☐	☐	☐	Disorderly
Stylish	☐	☐	☐	☐	☐	Not stylish
Satisfied	☐	☐	☐	☐	☐	Unsatisfied
Modern	☐	☐	☐	☐	☐	Old-fashion
Exciting	☐	☐	☐	☐	☐	Boring
Creative	☐	☐	☐	☐	☐	Not creative
Beautiful	☐	☐	☐	☐	☐	Not beautiful
Appealing	☐	☐	☐	☐	☐	Not appealing
Well-structured	☐	☐	☐	☐	☐	Unstructured
Outstanding	☐	☐	☐	☐	☐	Mediocre
Interesting	☐	☐	☐	☐	☐	Not interesting
Colorful	☐	☐	☐	☐	☐	Not colorful
Informative	☐	☐	☐	☐	☐	Not Informative
Enjoyable	☐	☐	☐	☐	☐	Not enjoyable
Magnificient	☐	☐	☐	☐	☐	Modest
Eye-catching	☐	☐	☐	☐	☐	Not eye-catching

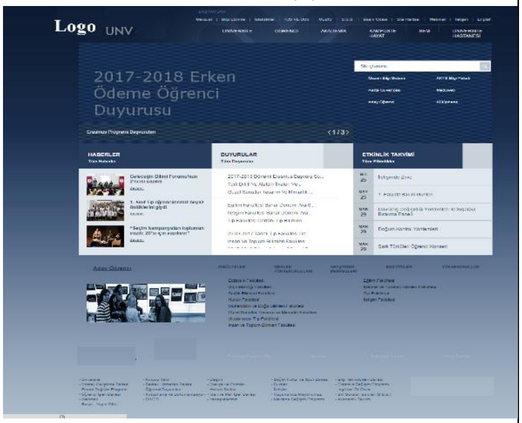
Domain (6)

How this website seems to you?

…………Very good … Not good…………..

	5 4 3 2 1	
Palin	☐ ☐ ☐ ☐ ☐	Mixed
Pleasant	☐ ☐ ☐ ☐ ☐	Not pleasant
Elegant	☐ ☐ ☐ ☐ ☐	Not elegant
Organized	☐ ☐ ☐ ☐ ☐	Messy
Adorable	☐ ☐ ☐ ☐ ☐	Not adorable
Fashion	☐ ☐ ☐ ☐ ☐	Unfashion
Orderly	☐ ☐ ☐ ☐ ☐	Disorderly
Stylish	☐ ☐ ☐ ☐ ☐	Not stylish
Satisfied	☐ ☐ ☐ ☐ ☐	Unsatisfied
Modern	☐ ☐ ☐ ☐ ☐	Old-fashion
Exciting	☐ ☐ ☐ ☐ ☐	Boring
Creative	☐ ☐ ☐ ☐ ☐	Not creative
Beautiful	☐ ☐ ☐ ☐ ☐	Not beautiful
Appealing	☐ ☐ ☐ ☐ ☐	Not appealing
Well-structured	☐ ☐ ☐ ☐ ☐	Unstructured
Outstanding	☐ ☐ ☐ ☐ ☐	Mediocre
Interesting	☐ ☐ ☐ ☐ ☐	Not interesting
Colorful	☐ ☐ ☐ ☐ ☐	Not colorful
Informative	☐ ☐ ☐ ☐ ☐	Not Informative
Enjoyable	☐ ☐ ☐ ☐ ☐	Not enjoyable
Magnificient	☐ ☐ ☐ ☐ ☐	Modest
Eye-catching	☐ ☐ ☐ ☐ ☐	Not eye-catching

Domain (7)

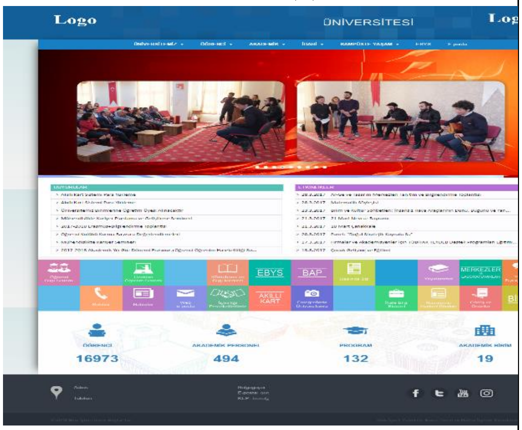


How this website seems to you?

…………Very good … Not good…………..

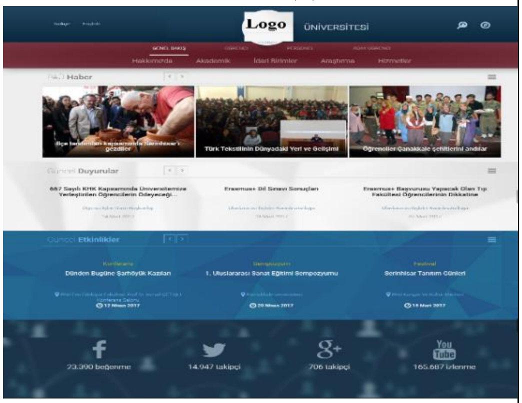
	5	4	3	2	1	
Palin	☐	☐	☐	☐	☐	Mixed
Pleasant	☐	☐	☐	☐	☐	Not pleasant
Elegant	☐	☐	☐	☐	☐	Not elegant
Organized	☐	☐	☐	☐	☐	Messy
Adorable	☐	☐	☐	☐	☐	Not adorable
Fashion	☐	☐	☐	☐	☐	Unfashion
Orderly	☐	☐	☐	☐	☐	Disorderly
Stylish	☐	☐	☐	☐	☐	Not stylish
Satisfied	☐	☐	☐	☐	☐	Unsatisfied
Modern	☐	☐	☐	☐	☐	Old-fashion
Exciting	☐	☐	☐	☐	☐	Boring
Creative	☐	☐	☐	☐	☐	Not creative
Beautiful	☐	☐	☐	☐	☐	Not beautiful
Appealing	☐	☐	☐	☐	☐	Not appealing
Well-structured	☐	☐	☐	☐	☐	Unstructured
Outstanding	☐	☐	☐	☐	☐	Mediocre
Interesting	☐	☐	☐	☐	☐	Not interesting
Colorful	☐	☐	☐	☐	☐	Not colorful
Informative	☐	☐	☐	☐	☐	Not Informative
Enjoyable	☐	☐	☐	☐	☐	Not enjoyable
Magnificient	☐	☐	☐	☐	☐	Modest
Eye-catching	☐	☐	☐	☐	☐	Not eye-catching

Domain (8)	How this website seems to you?



…………Very good … Not good…………..

	5	4	3	2	1	
Palin	☐	☐	☐	☐	☐	Mixed
Pleasant	☐	☐	☐	☐	☐	Not pleasant
Elegant	☐	☐	☐	☐	☐	Not elegant
Organized	☐	☐	☐	☐	☐	Messy
Adorable	☐	☐	☐	☐	☐	Not adorable
Fashion	☐	☐	☐	☐	☐	Unfashion
Orderly	☐	☐	☐	☐	☐	Disorderly
Stylish	☐	☐	☐	☐	☐	Not stylish
Satisfied	☐	☐	☐	☐	☐	Unsatisfied
Modern	☐	☐	☐	☐	☐	Old-fashion
Exciting	☐	☐	☐	☐	☐	Boring
Creative	☐	☐	☐	☐	☐	Not creative
Beautiful	☐	☐	☐	☐	☐	Not beautiful
Appealing	☐	☐	☐	☐	☐	Not appealing
Well-structured	☐	☐	☐	☐	☐	Unstructured
Outstanding	☐	☐	☐	☐	☐	Mediocre
Interesting	☐	☐	☐	☐	☐	Not interesting
Colorful	☐	☐	☐	☐	☐	Not colorful
Informative	☐	☐	☐	☐	☐	Not Informative
Enjoyable	☐	☐	☐	☐	☐	Not enjoyable
Magnificient	☐	☐	☐	☐	☐	Modest
Eye-catching	☐	☐	☐	☐	☐	Not eye-catching

Domain (9)	How this website seems to you?
	…………Very good … Not good…………..

	5 4 3 2 1	
Palin	☐ ☐ ☐ ☐ ☐	Mixed
Pleasant	☐ ☐ ☐ ☐ ☐	Not pleasant
Elegant	☐ ☐ ☐ ☐ ☐	Not elegant
Organized	☐ ☐ ☐ ☐ ☐	Messy
Adorable	☐ ☐ ☐ ☐ ☐	Not adorable
Fashion	☐ ☐ ☐ ☐ ☐	Unfashion
Orderly	☐ ☐ ☐ ☐ ☐	Disorderly
Stylish	☐ ☐ ☐ ☐ ☐	Not stylish
Satisfied	☐ ☐ ☐ ☐ ☐	Unsatisfied
Modern	☐ ☐ ☐ ☐ ☐	Old-fashion
Exciting	☐ ☐ ☐ ☐ ☐	Boring
Creative	☐ ☐ ☐ ☐ ☐	Not creative
Beautiful	☐ ☐ ☐ ☐ ☐	Not beautiful
Appealing	☐ ☐ ☐ ☐ ☐	Not appealing
Well-structured	☐ ☐ ☐ ☐ ☐	Unstructured
Outstanding	☐ ☐ ☐ ☐ ☐	Mediocre
Interesting	☐ ☐ ☐ ☐ ☐	Not interesting
Colorful	☐ ☐ ☐ ☐ ☐	Not colorful
Informative	☐ ☐ ☐ ☐ ☐	Not Informative
Enjoyable	☐ ☐ ☐ ☐ ☐	Not enjoyable
Magnificient	☐ ☐ ☐ ☐ ☐	Modest
Eye-catching	☐ ☐ ☐ ☐ ☐	Not eye-catching