THE ATTRIBUTES OF RELIABLE RECOMMENDER SYSTEM: ANALYSIS FROM CONSUMER PERSPECTIVE WITH DISCRETE CHOICE EXPERIMENT

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Thesis for the Master's Program in Logistics Management

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ETHICAL DECLARATION

By signing below, I attest that I am the only author of this thesis that I have conducted my work in accordance with academic rules and ethical behaviour at every stage from the planning of the thesis to its defence. I confirm that I have cited all ideas, information and findings that are not specific to my study, as required by the code of ethical behaviour, and that all statements not cited are my own.

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ABSTRACT

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Master’s Program in Logistics Management

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July, 2023

This dissertation aims to investigate the reliability of recommender systems (RSs) in online marketplaces from the consumer perspective. Literature review was conducted to learn the current state of the art in the area of RSs. In addition, drawing upon Information Processing Theory (IPT) helped to understand the decision-making process of consumers in online marketplaces. To achieve this goal, a mixed-method approach employed. In the first stage, consumers interviewed to determine the attributes that they considered significant in RSs. In the second stage, a discrete choice experiment (DCE) conducted to evaluate the reliability of the RSs. This research presents the results of a study on the attributes and levels of online shopping that affect the purchase decisions of consumers between the ages of 18 and 65, who lives in Türkiye. The results show that the most important attribute is the rating of the product, while the least important attribute is the number of comments. The comment with photo is the second most important, the way the item is recommended is the third, and influencer comments is the fourth. Furthermore, the findings of the study indicate that personalization is the most important attribute for consumers when it comes to the reliability of RSs. This study has important implications for the literature on online shopping and the use of RS. The results of this study have managerial implications that online players that utilize RSs.

Keywords: Online Marketplace, Recommendation System (RS), Discrete Choice Experiment (DCE), Information Processing Theory (IPT), Bayesian Design, Consumer Preferences

ÖZET

GÜVENİLİR TAVSİYE SİSTEMİNİN ÖZELLİKLERİ: AYRIK SEÇİM DENEYİ İLE TÜKETİCİ PERSPEKTİFİNDEN ANALİZ

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Temmuz, 2023

Bu tez, tüketici perspektifinden çevrimiçi pazarlardaki tavsiye sistemlerinin (TS) güvenilirliğini araştırmayı amaçlamaktadır. Mevcut TS alanındaki güncel durumu öğrenmek için bir literatür taraması yapılmıştır. Ayrıca, Bilgi İşleme Teorisi'nden (BİT) yararlanarak çevrimiçi pazarlardaki tüketicilerin karar verme sürecini anlamak amaçlanmıştır. Bu hedefe ulaşmak için karma yöntem yaklaşımı kullanılmıştır. İlk aşamada, tüketicilerle görüşmeler yapılarak TS'lerde önemli buldukları özellikler belirlenmiştir. İkinci aşamada, güvenilirliği değerlendirmek için kesirli seçim deneyi (KSD) uygulanmıştır. Bu araştırma, 18 ila 65 yaşları arasındaki ve Türkiye'de yaşayan tüketicilerin satın alma kararlarını etkileyen çevrimiçi alışverişin özellikleri ve düzeyleri üzerine bir çalışmanın sonuçlarını sunmaktadır. Sonuçlar, en önemli özelliğin ürünün puanı olduğunu, en az önemli özelliğin ise yorum sayısı olduğunu göstermektedir. Fotoğraflı yorumlar ikinci en önemli özellikken, ürünün nasıl önerildiği üçüncü ve etkileyici yorumlar dördüncü sıradadır. Ayrıca, çalışmanın bulguları, tüketiciler için kişiselleştirmenin TS güvenilirliği açısından en önemli

özellik olduğunu göstermektedir. Bu çalışma, çevrimiçi alışveriş ve TS kullanımıyla ilgili literatüre önemli katkılar sağlamaktadır. Ayrıca, bu çalışmanın sonuçları, TS kullanan çevrimiçi işletmeler için yönetimsel sonuçlar doğurmaktadır.

Anahtar Kelimeler: Çevrimiçi Pazar Yeri, Tavsiye Sistemi (TS), Kesikli Seçim Deneyi (KSD), Bilgi İşlem Teorisi (BİT), Bayes Tasarımı, Müşteri Tercihleri

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CF:	Collaborative Filtering
DCE:	Discrete Choice Experiment
EWOM:	Electronic Word-of-Mouth
IPT:	Information Processing Theory
RS:	Recommender System
WOM:	Word-of-Mouth
WWW:	World Wide Web

CHAPTER 1: INTRODUCTION

1.1. Research Background

Since Tim Bernes-Lee created the World Wide Web in 1989 at CERN, it has rapidly grown and evolved into four distinct phases: Web 1.0, Web 2.0, Web 3.0, and Web 4.0. The amount of content and users on the WWW (World Wide Web) have grown dramatically in recent decades. Users had access to knowledge and knowledge databases in web 1.0, but participation and information accessibility were constrained. Web 2.0 was invented by Dale Dougherty in 2002 (Majid and Verma, 2021). Web 2.0 is described by Mir and Hassan (2018) as a paradigm that promotes collaboration, information sharing, and user-centered design on the Web. In Web 2.0, however, users had the ability to interact and share new things with the people around them (Majid and Verma, 2021). Web 3.0 was invented by John Markoff in 2006 and is a combination of features from both phases (Majid and Verma, 2021). It is the internet age that is predicted to start in 2020 after the Web 3.0 era. It is revolutionary in terms of education and technological developments. Thanks to this internet technology, the use of physical disks would be discontinued and artificial intelligence operating systems interacting over virtual networks would be activated (Bock et al., 2020; Greengard, 2021). Along with the acceleration of technology evolution in every field, it also affected the retailing field. The increase in internet usage and online channels triggered the transformation of the retail industry (Verhoef et al., 2015). With the Internet, purely online retailers, such as Amazon and eBay, have emerged and so traditional retailers have evolved into multi-channel retailers to capture and not lose consumers (Min and Wolfinbarger, 2005; Pentina et al., 2009; Barkan and Koenigstein, 2016; Zhang et al., 2018). Competition in the industry has gradually increased as consumers began to use online channels. That's why many retailers have had to add an online channel to their own channels.

The development of the retail industry continues rapidly. The retail industry has continued to advance thanks to the rise of social media, mobile devices, and tablets over the past ten years (Zhang et al., 2018). The growth of these technologies enabling access to enormous volumes of data whenever has made it challenging for users to obtain pertinent information (Reinartz et al., 2019). The globe has transformed into an online marketplace. Hence, users have a hard time making decisions effectively when they have too much information (Duan et al., 2019). Previously, users tried different ways to filter this extra information. For example, according to Sernovitz (2010), a product can be researched using multiple platforms such as columnists, bloggers, live or face-to-face communication, e-mail, blog or forum posts, social media, etc. Recommender Systems (RSs) was developed to determine whether a user wants a specific item based on their preferences and by analyzing user behavior, or by suggesting the best items to the user. This helps users overcome the aforementioned challenge and select the appropriate option among numerous options (Chen, 2011).

In order to forecast a user's interest in an item based on pertinent information about things, users, and interactions between them, RSs are programs that attempt to recommend items such as products or services that are best suited to certain users, such as individuals or corporations. According to Bobadilla et al. (2013), the goal of creating RSs is to extract the most pertinent data and services from large amount of data, hence lowering information overload and delivering individualized services. The RSs are designed to help users who lack the knowledge or time to assess all of the options that a website offers. In their most basic form, all RSs offer users customized and arranged lists of stuff.

Using the following algorithm as an example, we can illustrate how RSs work: "Consumers who bought this product also bought..." According to Goldberg et al. (1992), RSs were first imagined during the start of the 1990s. The ability to predict a user's preferences and interests is the most crucial aspect of the RSs, according to Resnick and Varian (1997), who also state that they examine a user's activity to develop customised recommenders. Not just when purchasing something, but even when watching a video, consumers could be recommended other videos that they might find interesting. Applications of RSs include e-commerce, e-business, and e-government as well as media types like, music, television, websites, shows, books, documents, conferences, movies, and tourism hotspots (Frias-Martinez et al., 2009; Lu et al., 2015; Jugovac and Jannach, 2017; Cui et al., 2018; Taghavi et al., 2018; De Medio et al., 2020). Generally speaking, RSs assist users in finding information, goods, or services such as books, clothing, music, and TV shows by gathering and analyzing user recommendations (Kim et al., 2010; Lee et al., 2010; Taghavi et al., 2018;

Andjelkovic et al., 2019). Additionally, a lot of media companies presently create and disseminate operating systems as a component of the services they offer to its users. For instance, the first team to dramatically raise the performance of their RSs will get a $1 million reward from Netflix, a website that offers on-demand streaming media (Sousa et al., 2023).

The World Health Organization (WHO) classified COVID-19, a coronavirus-induced sickness, as a pandemic disease on March 11 (WHO, 2020). COVID-19 originated in Wuhan, China in December 2019 and quickly spread throughout the world. The New Type of Coronavirus (COVID-19) epidemic, in addition to being a health crisis, is a global economic crisis that has seriously shaken the world economy (Yu et al., 2021). The measures taken by the states to prevent the epidemic have brought the problems of the world economy to a level that can be defined as "global depression" (Yu et al., 2021). Social distance, curfews and daily life routines that are blocked and banned due to the pandemic have brought the activities of many sectors from the food sector to the manufacturing sector, from the transportation sector to the textile sector, from the education sector to the tourism sector, and especially have seriously affected the tourism and retail industry (Baker et al., 2020). As a result of the research conducted by Shaikh (2020), this situation will change the purchasing behavior of consumers until the COVID-19 process is completed and normal life is resumed. It has been emphasized that important arrangements should be made for those who do not affect the economy, who cannot spend, who have to stay at home, who like to try different dishes in different regions, who are fond of shopping, and for the audience of events such as cinema and theater (Shaikh, 2020). Today's technological advances and the worldwide effective Covid-19 pandemic have increased the importance of e-commerce sites and stores have offered their products to users through e-commerce sites (Din et al., 2022; Priambodo et al., 2021). According to the first 6 months data of the T.R. Ministry of Commerce, Department of Electronic Commerce, in March, April and May 2020, when the pandemic began to be effective in our country, e-commerce sites grew by 19% compared to the previous year, and the number of orders they received was 292 million during the pandemic period, this number has increased. The proportion of e-commerce to overall trade in the first half of 2021 was 17.6%. With the controlled normalization in the coronavirus (COVID-19) pandemic, this rate was 15.2% in June. The volume of e-commerce in our nation surged by 75.6% during the first half of 2021 compared to the same time in the previous year, reaching 161 billion TL, according to 2021 data. Orders rose from 850.7 million in the first half of 2021 to 1 billion 654 million, a 94.4 percent rise. However, with the popularization and spread of e-commerce sites, it has become more difficult for users to find the most suitable options for themselves among a large number of products. For this reason, systems that enable individuals to obtain products from specialized information have gained importance. In this way, the user both deals with information and enables him/her to reach the product he/she is looking for in a shorter time. As a result, RSs have gained heightened significance, consequently elevating their status as one of the prevailing subjects in contemporary discourse.

1.2. Research Purpose and Goals

Studies in this area have increased since the RSs gained so much popularity (Milano et al., 2020; Batmaz et al., 2019). However, there were relatively few research that were consumer and reliability focused, and the majority of studies in the literature concentrated on just one type of RSs (Tarus et al., 2018; Guo et al., 2020). Many researchers have made a study to increase the reliability of the RSs with mathematical algorithms. In addition, no studies have been conducted on the reliability of consumer-oriented studies. For example, Riyahi and Sohrabi (2020), Betancourt and Ilarri (2020), Li et al. (2015), and Bhattacharya et al. (2016) generated a new RSs by using the text mining approach. Xu et al. (2018) studied the impact of adjective attributes in user reviews on RSs. Zhang et al. (2018), Ahmadian et al. (2022), Ahmadian et al. (2022) and Da'u et al. (2020) aimed to develop a more reliable RSs using the deep learning approach. Najafabadi et al. (2017), Moradi and Ahmadian (2015) and Ahmadian et al. (2018) argued that improving the reliability of collaborative filtering, a type of RSs, with cluster analysis techniques. The Slope One Algorithm was employed by Jiang et al. (2019) in an effort to investigate the trust-based collaborative filtering algorithm RSs.

Despite the rise in RS articles published in recent years, it was decided to conduct this study to thoroughly examine the applications of RSs by carrying out a consumer perspective study of the reliability of RSs in order to fill the gap in the literature. It is advised to perform research on this topic because the RSs is depicted as the replacement for electronic word-of-mouth communication in Verma and Yadav's

(2021) publication.

This study's goal is to fill this gap in the literature. Research involving consumers who were using the RSs was carried out to meet this objective. To acquire thorough data for this investigation, a variety of strategies are used. In the beginning, consumers are interviewed because this method provides more detailed information (Roy et al., 2015). Various factors that affect the RSs' reliability have been established by prior study. The initial phase of conducting consumer interviews aims to reveal the RSs' most important attributes. A discrete choice experiment (DCE) is then put into practice. It is significant to remember that the DCEs' included features could be changed in light of new information learned from the consumer interviews. As a result, a survey will be carried out that takes into account both the results of the interviews and the body of prior research.

1.3. Research Questions

The establishment of significant research questions serves as a crucial and fundamental guideline for the measurement and assessment procedure, which is the goal of this dissertation. For the evaluation process, specific research questions were created to investigate the features that, in the eyes of the consumer, make the RS trustworthy in online marketplaces and to gauge the importance that consumers place on those features. These are the dissertation's research questions:

RQ1. What are the features that make the recommender system reliable from consumer perspective in online marketplaces?
RQ2. Which features are mostly preferred by the consumers for reliability that use a recommender system in online marketplaces?

1.4. Originality and Significance of the Study

The importance of consumers in the online marketplace has been the subject of many different studies (Maier and Wieringa, 2021; Orsolini et al., 2015; Kafkas et al., 2021; Qi et al., 2016). According to the research of the Interactive Advertising Bureau (IAB) in Türkiye, in the first half of 2022, when looking at Digital Media Investments in Türkiye based on the 'device type where the advertisement is displayed' filter, it was observed that Mobile devices accounted for a 76% share. Mobile device media investment, which had a 5.369 billion TL investment in 2021, has reached 10.643 billion TL." (IAB Türkiye AdEx-TR 2022 Report). The increasing interest in this field from day to day has also accelerated the research in this field.

One significant area of study that has played a crucial role in comprehending how individuals process information across diverse domains is the Information Processing Theory (IPT). Developed by George Armitage Miller in 1956, IPT is a cognitive theory that aims to explain the reception, processing, storage, and retrieval of information in the human mind. Drawing an analogy to a computer, this theory suggests that the brain follows a predetermined order of steps: receiving input, processing information, and delivering an output (Miller, 1956). As a result, the processing of information is considered to be similar in humans.

The widespread applicability of IPT is evident in various fields such as marketing (Goyette et al., 2019), psychology (Sui and Liu, 2020), technology adoption (Yang et al., 2020), and management (Bieńkowska et al., 2021). Moreover, the theory has found its way into the realm of e-commerce, where researchers have utilized it to explore the impact of personalization on websites on consumers' revisit intention (Desai, 2019), understand how telepresence affects consumers (Lim and Ayyagari, 2018), and investigate the influence of personalized e-commerce on consumers' purchasing intention (Pappas et al., 2017). It has also been employed to gain insights into online purchase decision-making processes (Gao et al., 2012).

The Information Processing Theory continues to be a valuable framework in clarifying the complexities of consumer behavior and decision-making, particularly in the ever-evolving landscape of e-commerce. Researchers across disciplines are likely to draw upon its principles to deepen their understanding of human information processing in the context of the online marketplace.

Desai (2019) employed IPT to understand the impact of personalization on websites on consumers' revisit intention. In this study, the researcher applied IPT to examine how the process of receiving personalized information from websites influences consumers' likelihood of revisiting those websites. Lim and Ayyagari (2018) utilized IPT to understand the impact of telepresence on consumers. The authors utilized IPT to investigate how the mental processes involved in perceiving and processing telepresence (the feeling of being present in a virtual environment) affect consumer behavior. Pappas et al. (2017) used IPT to understand the impact of personalized e-commerce on consumers' purchasing intention. This study employed IPT to explore how personalized e-commerce experiences affect the cognitive processes involved in consumers' decision-making and their intention to make a purchase. Gao et al. (2012) applied IPT to understand online purchase decision-making. The researchers employed IPT to analyze how individuals receive, process, and store information when making decisions about online purchases. By mentioning these examples, the paragraph supports the idea that IPT has been successfully applied in various fields such as marketing, psychology, technology adoption, and management. These studies demonstrate the usefulness of IPT in understanding cognitive processes related to information reception, processing, and storage. Therefore, it is appropriate to consider using IPT in the study being discussed.

Drawing from the examples mentioned above, it is evident that the IPT has proven to be a valuable framework in understanding cognitive processes in various fields, such as marketing, psychology, technology adoption, and management. Through the application of IPT, researchers have gained valuable insights into how consumers receive, process, and store information, and how these processes influence their behaviors and decision-making. The successful use of IPT in these diverse areas demonstrates its versatility and effectiveness as a tool for investigating human cognition. However, while IPT has shown promise in shedding light on information processing, it is not the only method available for gaining a deeper understanding of human experiences and behaviors. Another powerful technique used across multiple research disciplines is the interview method. This qualitative data collection approach provides researchers with an opportunity to engage in meaningful conversations with individuals, allowing for a comprehensive exploration of their thoughts, feelings, attitudes, and experiences related to a particular topic or situation. By employing both IPT and interviews, researchers can enrich their investigations and gain a more holistic understanding of the complex cognitive processes and behaviors of individuals.

The interview technique serves as a valuable tool in various research fields, including marketing, psychology, technology adoption, and management. Interview is a data collection technique used in qualitative research (Moser and Korstjens, 2018; Busetto et al., 2020). An interview is a conversation whose purpose is to collect information (Powney and Watts, 2018). In other words, interviewing is the activity of understanding the feelings and thoughts of the individuals included in the research about a topic or situation. Interviewing is an effective technique for understanding people's feelings, thoughts, attitudes, experiences and complaints (DeJonckheere and Vaughn, 2019). The interview technique includes all efforts aimed at obtaining the desired data to be reached (DeJonckheere and Vaughn, 2019). According to this description, interviews conducted between two or more people around a specific purpose and in a specific order (DeJonckheere and Vaughn, 2019). In-depth understanding of the participant's perspective on the pertinent problem or circumstance is the goal of the interview (Fleming, 2018).

In this study, semi-structured interviews were used. There were various factors considered before deciding on a semi-structured interview for this study. A halfway ground between organized and unstructured interviews are represented by semi-structured interviews. In this type of interview, the interviewer follows a general roadmap but has the flexibility to modify the questions based on the characteristics of the interviewees, thereby exploring different dimensions of the subject within a broader framework (Punch, 2013). Semi-structured interviews utilize an interview form that consists of a set of pre-designed questions. However, during the interview, the interviewer can delve into specific details or address any missing points by adding or changing questions (Berg and Lune, 2015). This flexibility allows for obtaining comprehensive information that aligns with the research objectives (Punch, 2013). The semi-structured interview method has been widely employed in e-commerce studies in the literature. For instance, Gedikli et al. (2014) employed semi-structured interviews to assess the impact of different explanation types on users' responses to recommendations. Similarly, Virdi et al. (2020) utilized interviews to investigate contextual information influencing the selection and decision-making process in RSs within digital libraries. Overall, semi-structured interviews are employed in this study provides a balance between the structure and flexibility necessary to obtain detailed and comprehensive insights from the participants, aligning with the goals of the study and contributing to the existing corpus of information in the field of e-commerce.

As the preceding paragraph highlighted the significance of semi-structured interviews in e-commerce studies, the focus now shifts to exploring another research methodology that has not been extensively investigated in the context of online shopping and RSs. The use of DCEs in the area of online shopping and RSs has not been explored in previous studies. DCEs have been widely used in market research and economics of transport, environment and health in recent years (Ryan et al., 2012; Goranitis et al., 2021; Liu et al., 2021). Measurement of stakeholder preferences in the healthcare industry has been more crucial recently as patient-centered policies have been implemented in treatment alternatives, medical research, technology evaluation, and legislative laws (Janssen et al., 2017; Sumpton et al., 2022). To the best of our knowledge, DCE was not used in any of the studies in the area of online shopping and/or RSs. In the light of studies in the field of health, it has been revealed that DCEs would play an important role in determining consumer choices. It would be the first study done in this area DCEs and combination of IPT, interview and DCEs.

1.5. Structure of the Thesis

The introduction section of this thesis, Chapter 1, discusses the goals and objectives of this investigation. On the other hand, Chapter 2 is entirely devoted to the literature assessment of the prior studies, the development of the model, and its pertinent metrics. Chapter 2 also discusses consumer preferences, consumer behavior, and the RS in the context of online buying. The theoretical underpinnings and methodology of the variables employed in this study are discussed in Chapter 3. The data collection method survey advancements are discussed in Chapter 4, along with early tests, pilot studies, and the Bayesian design approach. In Chapter 5, the Bayesian design framework-based data analysis is demonstrated in terms of the study's validity and reliability. The limitations of this study are discussed in Chapter 6 together with their theoretical and practical implications. It also makes reference to the results section and gives a general overview of the needs and constraints for future study.

CHAPTER 2: LITERATURE REVIEW

2.1. Overview of RSs

In recent years, many people have encountered the phenomenon known as RSs. In this part of the study, the concept of a RS is examined in detail. In this context, first of all, RSs would be defined, after mentioning its origin and benefits, the types of RSs are mentioned. After mentioning the types of RSs, this part of the study would be concluded by mentioning the dynamics that require these systems and theoretical background.

2.1.1. Definition of RSs

Every day, people are faced with dozens of decisions such as what clothes to wear, which movie to watch, which song to listen to, which book to read, which restaurant to visit and they have to make these decisions very quickly because these decisions are constantly repetitive. In the past, people relied on suggestions from friends, ads, newspapers, or magazines to make their selections. However, the scope of and potential for bias in these suggestions is limited (Adams et al., 2020; Smith et al., 2020). Because of this, since they can benefit from both acquaintances and other individuals, computer-aided technologies can provide suggestions from a wide range of alternatives (Jannach et al., 2011).

RSs make suggestions to users with the assumption that they will find the suggestions appealing. These are systems that enable users to be aware of different news and products while shopping, reading news or watching movies on the internet, and thus discovering new products. Once you start looking for a product on any shopping site, products similar to the products examined can appear both on the site we shop and while browsing the internet, for example, in the advertisements section of a news site. RSs have been used in various fields, including movies (Diao, et al., 2014; Yi et al., 2017; Kermany and Alizadeh, 2017; Cintia Ganesha Putri et al., 2020; Parida et al., 2021), music (Oramas et al., 2017; Andjelkovic et al., 2019; Jazi et al., 2021; Okada et al., 2021), news (Liu et al., 2010; Saranya and Sadhasivam, 2012; Chen et al., 2017; Zihayat et al., 2019; Feng et al., 2020), books (Frias-Martinez et al., 2009; Tewari et al. 2014; Tian et al., 2019; Rana and Deeba, 2019), location (Zhang et al., 2015;

Setiowati et al., 2018; Mohammadi and Rasoolzadegan, 2021) and products (Park and Chang, 2009; Baum and Spann, 2014; Hwangbo et al., 2018; Pan et al., 2020).

According to Ricci et al. (2011), RSs can rank items that are best suited for a user or forecast items that are invisible to the user. While browsing online shopping, movie, game sites, "best-selling product", "other products in this product group", "best-selling books", "users also viewed these products", "games or movies you may like" are displayed at the bottom or side of the pages, "news that may be of interest to you", such as "news that may be of interest to you" by the websites, we are advised by the products or messages they are related to (Davis et al., 2020; Clark et al., 2021). The objective of both types is to recommend to users the products that will work best. Considering that we spend most of our time on the Internet in our daily lives, apart from our sleeping and working lives, it is inevitable that the Internet would be a huge commercial market. In this market, the product and service recommenders offered to the visitors according to the type of websites would both facilitate the work of the visitors and provide more product sales.

Following that, RSs started to expand quickly. In addition to the scientific community, corporations and industry have shown a lot of interest in RSs. Well-known companies that have been using RSs to recommend products to its clients for more than ten years include Amazon.com and Netflix (Ekstrand et al., 2011).

In the literature, the factors that are important in the RSs for consumers are the techniques of RSs that is collaborative filtering (Goldberg et al., 1992; Xu et al., 2018; Hwangbo et al., 2018; Iwanaga et al., 2019; Sun et al., 2019; Rana and Deeba, 2019; Shin, 2020) and content-based filtering (Lombardi and Vernero, 2017; Xu et al., 2018; Sun et al., 2019; Shin, 2020), electronic Word-of-Mouth (eWOM) (Baum and Spann, 2014; Liu and Yang, 2016; Hayashi et al., 2017; Schmalz et al., 2018; Varma and Yadav, 2021) and influencer / celebrity / expert comments (Maity, 2014; Park et al., 2019; Wang et al., 2020; Feng et al., 2021).

2.1.2. RSs in E-Commerce

RSs have been used for a long time in most platforms that serve on the Web, especially e-commerce. RSs aim to alleviate the problem of information overload on users by offering personalized content that may be of interest to users. Academic studies, which gained momentum in the 1990s, supported the development of RSs by testing the applicability of the methods obtained by the e-commerce sector on real-time data.

E-commerce RSs uses the demographic characteristics of the user to get more consistent recommendation results. Amazon, eBay, Netflix etc. such as online applications and stores benefit from the past purchases or behaviors of the user (Beel et al., 2015; Barkan and Koenigstein, 2016). The development created by e-commerce sites that sell retail products and services, starting with Amazon and Netflix, has allowed the emergence of RSs in the entertainment industry such as Itunes, last.fm, Pandora and IMDB, rottentomatoes, Metacritic, where the tastes and preferences of the user are at the forefront. Amazon took a leading position in the sector with its establishment in 1994 and developed algorithms on collaborative RSs in 1998 (Robinson et al., 2021). It published its success in 2003, with its wide product range and user profile, and instantaneously offering small-scale product suggestions for each user among many products. (Smith and Linden, 2017). Netflix, on the other hand, made one of the biggest breakthroughs and organized a competition with a grand prize, and as a result of this competition, it showed the importance of such systems with a success rate of over 10% (Bell and Koren, 2007). Among the well-known websites using Content Based Filtering systems are IMDB (http://www.imdb.com) and Pandora (http://www.pandora.com) (Rafter, 2010). IMDB is known as the movie database on the internet. When using the IMDB RS, it takes into account the content of the movies (director, actor, keywords, theme ...) that the users liked before. Pandora, on the other hand, uses a Content Based Filtering structure developed on the Music Genome project (Castelluccio, 2006; Joyce, 2006).

Two of the most frequently visited websites using Collaborative Filtering techniques are those of Amazon and Last Fm (Wang et al., 2018). Looking at the RS run on Amazon.com, it is seen that it is a typical RS to begin with (Hardesty, 2019). Considering that there is a user who wants to buy a book, the books that have the most similar summary with the book they want to buy are listed (Hardesty, 2019). In addition to this process, the users who bought that book are also examined and the books that the users who buy this book buy together with the book are also taken into consideration (Hardesty, 2019). In addition to these, in order to provide more precise recommendations, the system asks users to rate the books they have read (Hardesty, 2019). Thus, more accurate suggestions are produced by taking into account the information about which type of books the user likes (Hardesty, 2019). Last.fm, on the other hand, recommends music to users with the help of its RS (Yang et al., 2021). Apart from Last.fm, there is also a music RS called AudioScrobbler (Alaimo and Kallinikos, 2021). In these RSs, users with similar music tastes are determined by comparing the music they have listened to from the radio or from their own music lists (Alaimo and Kallinikos, 2021). Music suggestions are made considering the neighbors of the user (Yang et al., 2021). In this system, scientific studies have developed within the framework of a mutual benefit line with the IT companies that provide the opportunity to use large data sets (Yang et al., 2021; Alaimo and Kallinikos, 2021; Hardesty, 2019).

Amazon took a leading position in the sector with its establishment in 1994 and developed algorithms on collaborative RSs in 1998 (Linden et al., 2003). It published the success it achieved with its presentation in 2003. (Smith and Linden, 2017). Since RSs were adopted by Amazon, several e-commerce and internet platforms have adopted them. Increasing sales volume is a key justification for doing this. Many companies, such as Net Perceptions and Strands were established to provide recommendation technology and services to online retailers. (Ekstrand et al., 2011).

Netflix, on the other hand, made one of the biggest breakthroughs and organized a competition with a grand prize, and as a result of this competition, it showed the importance of such systems with a success rate of over 10% (Knudsen et al., 2021). Another application of e-commerce RSs provides feedback to other users with the help of the product scores they receive from their users. For example, iTunes asks its users to give an evaluation score between 1 and 5 for the music or albums they purchase, and these scores are evaluated in the background and used to create consistent product recommendations for subsequent users (Lu et al., 2015).

RSs provide many benefits to both users and parties offering objects. Some of them could be listed as follows (Jannach et al., 2011; Ricci et al., 2015; Rivas et al., 2019; Milano et al., 2021);

- *Increases the number of products sold:* This feature is probably the most important benefit of these systems for a commercial site. Since the proposed product is likely to be a product that the online consumers both need and want, the probability of the consumer buying this product would increase, and this would have a positive effect on sales.

- *More variety of products are sold:* One of the biggest problems of commercial sites is the problem of constantly selling similar products to the same consumers. RSs have reduced the effects of this problem by suggesting products that are completely different from these products in addition to the products consumers are interested in.
- *Increases the consumer's trust:* As the consumer finds the products offered by the system interesting, relevant and close to him/herself, the consumer's trust in the system and the company would increase over time.
- *Increases consumer loyalty:* When user goes to a store, if the seller knows him/her and could predict more or less what he/she wants, he/she likes to go to that store, and when he/she needs a product, the first place that comes to his/her mind is that store. Based on this example, if an e-commerce site knows its consumer online, knows his/her personal preferences, and can recommend products in line with the consumer's desire; in short, if it could make the consumer feel valuable, they would use this site again when he/she needs it.

2.2. Techniques of RSs

Classes of web applications that aim to predict the behavior that users may give to the options they encounter are called RSs. These systems are among the applications with high popularity today. It has started to be used in many areas from products on e-commerce sites like Netflix, Spotify, eBay, Amazon etc. to music and is still being used. (Barkan and Koenigstein, 2016). Online application and electronic commerce systems such as online applications and electronic commerce systems use RSs to offer their users the products they like or may like in a personalized way (Alamdari et al., 2020). The approaches most frequently employed in RSs would be outlined in this section.

2.2.1. Collaborative Filtering (CF)

CF was first used in the Xerox research center for email filtering in the 1990s. The application created for this purpose used by a small group of users and has been successful. In general, RSs for books, movies, music, e-commerce products, etc. frequently use collaborative filtering (Hwangbo et al., 2018). According to Yun et al. (2018), CF is the process of selecting or ranking items based on the views of other people. In the literature, there are studies applied with the CF method. In the StreamRec (Chandramouli et al., 2011) system, users were grouped according to similar news they read, and it was emphasized whether they read the news again or for the first time. If he/she is reading the news again, he/she makes an evaluation accordingly and the user groups are re-created.

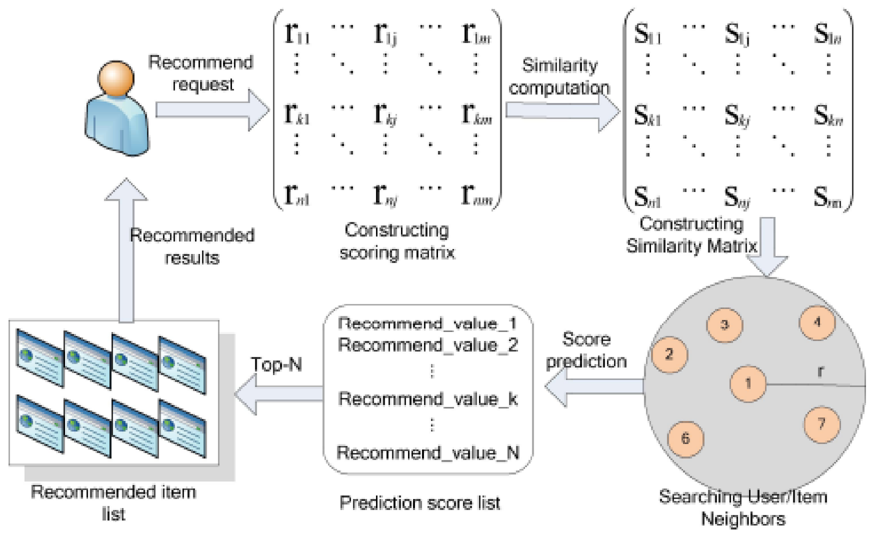


Figure 1. General Recommendation Process of Collaborative Filtering Algorithm (Source: Li et al., 2019)

In their articles, Saranya and Sadhasivam (2012) applied the CF method by constantly updating the user profiles of the personalized news RSs dynamically. Schafer et al. (2007) suggested that CF presents new recommendations to users by filtering and evaluating these compiled opinions and evaluations. In Figure 1 you can see the general algorithm of CF, but this RS model consists of 2 types. Examples of CF Algorithms:

- *User-User CF:* In this method, the system evaluates a user's interest in an item. Attempts to associate similar consumers and present products based on products chosen by consumers (Ekstrand et al., 2011; Charu, 2016; Iwanaga et al., 2019). Calculates this item's scores taking into account other users in the user's neighborhood. Although it requires time and resources, it is highly successful. This kind of filtering needs examining the data from both sorts of consumers; in addition, additional users who have similarly rated things are in the user's vicinity (Shah et al., 2017). Consequently, it is challenging to execute this method across broad platforms.

- *Item-Item CF:* It is a method developed by Amazon. The new algorithm is very similar to the old one, but it concentrates on product similarity rather than consumer similarity. Instead of scoring, implicit feedback such as clicks, impressions, visited sites can also be considered as variables. With this algorithm, similar items can be easily suggested to the consumer who buys any item (Ekstrand et al., 2011; Charu, 2016; Iwanaga et al., 2019). The fundamental goal behind this approach is to make sure that the products that a user purchases or views on a product detail page are recommended to other users who share similar interests by taking into account similarities (Barkan and Koenigstein, 2016). In comparison to user-user collaborative filtering, it involves fewer time and resources (Sánchez-Moreno et al., 2019).

2.2.2. Content-Based approach

One of the first forms of information processing is regarded as being content-based RSs. Contrary to many systems that are already in use and overlook content information, the usage of content information has shown to be particularly beneficial in processing and reaching information (Jones, 2005; Shu et al., 2018). In content-based approaches, a database of user profiles and product features is used. The products that this user has previously reviewed are used to generate a profile of the user if there is a lack of information regarding their profile. The user is then given recommendations for products that fit this profile (Chen et al., 2011; Garca-Pedrajas et al., 2011; Geetha et al., 2018).

There are studies that apply the content-based filtering approach with different methods. This method relies on product descriptions and user profiles. A content-based RS uses keywords to describe products and user profiles to determine the categories of goods that consumers are interested in (Brusilovsky, 2007; Charu, 2016; Javed et al., 2021). In other words, it suggests goods that are comparable to goods the consumer has previously liked and goods they are now reviewing. To illustrate, in another study, Liu et al. (2010) took a different approach and calculated the time users spent on articles. In their study, Pazzani and Billsus (2007) performed the suggestion process by paying attention to the latest news read by the users. In their study published by Suchal and Navrat (2010), they defined the documents and users to be proposed as virtual elements, created document user clusters, found users who were similar to each other, reached documents through similar users and performed the suggestion process.

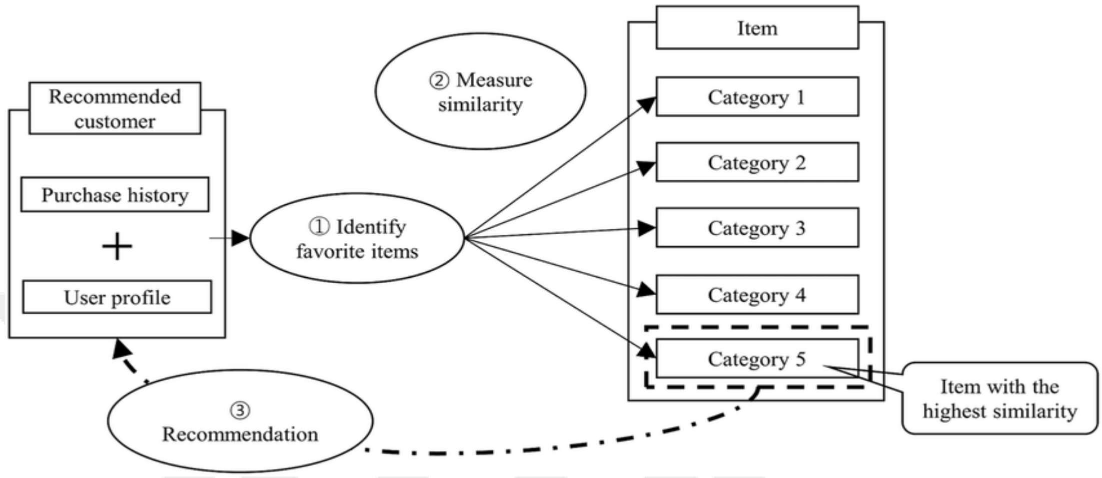


Figure 2. General Recommendation Process of Content Based Algorithm (Source: Lee and Lee, 2018)

This filtering technique is based on the description of a product and the details of user-preferred options (Figure 2). Keywords are used to describe the product in a content-based RS. The goal of algorithms is to suggest goods that users might enjoy based on past preferences. If you enjoy one product, you probably will like another one that is similar, according to the theory behind content-based filtering.

2.3. Factors that Affecting RSs

In the literature results on RSs, there are some elements that both affect this system and make it work more effectively. These factors are; electronic Word-of-Mouth (eWOM) and expert or celebrity reviews. The factors mentioned in this section explained in detail.

2.3.1. Electronic Word-of-Mouth (eWOM)

Traditional WOM has been superseded by eWOM as a result of the integration of the internet in all spheres of life. According to Thurau et al. (2004), Baum and Spann

(2014), Verma and Yadav 2021) and other sources, eWOM refers to the good or negative thoughts of future, present, or former consumers regarding a product or company. These comments are made available to many people and organizations via the internet. Chevalier and Mayzlin (2006) contend that online user reviews have taken the place of traditional types of word-of-mouth (WOM) advertising regarding various product features and are now a significant source of information for consumers. Although eWOM shares many traits with conventional WOM, it presents an entirely different viewpoint on WOM (Almana and Mirza, 2013; Yuan et al., 2020).

In eWOM consumer reviews, consumers only need to interact with their computer to post product reviews. Their views are widely and easily accessible to other consumers. Other consumers can access them to search for information about the type of products examined (Sen and Lerman, 2007). In other words, eWOM results from a number of consumers discussing a certain set of product attributes in order to provide others a different viewpoint on the desired product (Sparks and Browning, 2011; Pyle et al., 2021).

Online shoppers must rely on the descriptions of the products on the website in order to make purchases because they are unable to physically contact or smell items as they could in a real store (Park et al., 2007; Kripesh et al., 2020). As a result, the views expressed on the websites are either favorable views endorsing the product or unfavorable views opposing it (Sen and Lerman, 2007). The negative eWOM will have a greater impact on the buying choice than the positive eWOM (Chang and Wu, 2013). Therefore, when developing successful internet marketing strategies, businesses should take into account the impact of eWOM on consumers' purchasing intentions (Park and Lee, 2009; Alwan and Alshurideh, 2022).

Many studies on marketing draw attention to the effect of eWOM on consumption. Because eWOM affects the purchasing decision, decision process and purchase intention in many ways. In their study, Thurau and Walsh (2003) obtained five factor dimensions as "acquiring information about purchases", "social guidance through information", "community membership", "remuneration" and "learning from the consumer" by factor analysis and eWOM '. They determined that the most influential factor is acquiring information about the purchase. Almana and Mirza (2013) combined online consumer opinions under 3 factors: "features of opinions", "features of opinion writers" and "features of the website where the opinions are presented". The study's findings revealed that the qualities of products with high ratings and views had the greatest influence on consumer choice. Additionally, consistency, the volume of online reviews, and the date of the reviews are crucial considerations when making a purchase (Almana and Mirza, 2013; Baum and Spann, 2014; Ventre and Kolbe, 2020). Poon et al., (2014) examined the impact of eWOM on booking intention in five dimensions: “perceived eWOM credibility”, “positive online reviews”, “negative online reviews”, “eWOM user expertise” and “user's eWOM concern”. However, they found that “perceived eWOM credibility” and “negative online opinions” did not statistically significantly affect booking intention.

Online consumer opinions play a dual role for consumers as opposed to advertising messages. Both the informer and adviser roles are positively related to the consumer's intent to purchase (Park et al., 2007; Baum and Spann, 2014).

Studies have typically concentrated on consumer information sharing factors. Cheung et al.'s (2008) investigation on the relationship between source dependability and opinion quality on the utility of information and its impact on knowledge adoption shows that little attention is paid to the aspects that influence consumers to benefit from online consumer opinions in their purchasing decisions. They concluded that the consumer's decision to accept information in online communities is strongly and significantly influenced by the utility of the information.

Online consumer opinions, which appear as an important element of marketing in all sectors, are also effective in the tourism sector. We can see that the majority of consumers read online vacation reviews before making a purchase, and they do so for two different purposes: to look for recommended activities and to check for any potential newly published reviews (Chen et al., 2015). In their study, Viglia et al. (2016) discovered a correlation between an increase in the occupancy rate of 7.5 points and a one-point increase in the average review score of a published opinion on online platforms, which was converted between 1 and 10. This involves using internet review factors into models created to determine the profitability of hotels. The research adds to the body of knowledge on eWOM by examining a less-studied hotel performance metric (hotel occupancy) using a thorough methodology that considers multiple hotels and online review sources (Viglia et al., 2016).

In the literature, Thurau and Walsh (2003) revealed the reasons why consumers get the online opinions of other consumers from web-based consumer opinion platforms. An empirical study of approximately 2,900 German platform users showed that readers find informational content particularly important because it enables them to make better purchasing decisions and complete their searches in less time. An online sample of about 2,000 consumers was used in the Thurau et al. (2004) study to collect data on the nature and applicability of the motivations behind online consumer reviews. The investigation that followed revealed that the main driving forces behind eWOM behavior are consumers' desire for social connection, desire for financial incentives, concerns for other consumers, and their capacity to increase their own sense of self-worth. Park et al. (2007) investigated how the quantity and quality of consumer opinions affect purchase intention. In the study, in which 352 volunteer university students participated, it was found that the quality of online comments had a positive effect on consumers' purpose of purchasing, and that the more the number of reviews, the higher their purchase intention. Khammash (2008) tested the motivations for reading online opinions and their impact on consumer behavior in a large-scale quantitative survey by administering it to 1010 people. He concluded that online reviews are read mostly to benefit from consumer experiences and positive eWOM influences purchase intention more than negative eWOM. Cheung et al. (2009) investigated how informative and normative determinants affect the perceived reliability of online consumer recommendations. In a widely used consumer forum in China, users were invited to participate in the survey via e-mail and efficient responses were received from 159 people. As a result, it was found that the perceived eWOM reliability had a positive effect on the adoption of the eWOM review. The study by Almana and Mirza (2013) examines how Saudi residents' online purchase decisions are impacted by online reviews. According to survey results, eWOM has a significant impact on Saudi Internet buyers, and a larger proportion of them turn to online forums when deciding whether or not to make an online purchase. Finally, the main purpose of the study of Poon et al., (2014) is to identify the eWOM factors that trigger hotel consumers' reservation intention. The questionnaire was hand-delivered to 500 consumers selected from among 10 selected hotels in Kuala Lumpur, Malaysia. The three eWOM elements that influence the reservation intention are positive eWOM, consumer experiences, and consumer involvement, according to the findings of the regression study.

2.3.2. Number of Comments

The quantity of comments in an RS can be greatly influenced by a variety of factors, including as the popularity of the items being recommended, the number of users using the system, the frequency of suggestions, and the user interface design (Tintarev and Masthoff, 2012). RSs that permit users to remark and offer feedback on recommendations typically have more comments than those that do not. These comments can offer insightful data regarding the effectiveness of the suggestions and the user experience, which can help the system perform better over time (Herlocker et al., 2000). It is crucial to remember that the quantity of comments might not be a good gauge of the system's efficacy or utility. Other measures like correctness, relevance, and user (Tintarev and Masthoff, 2012).

The number of comments in a RS can vary depending on several factors, including (Netflix. (2021). How Netflix Recommendations Work; TripAdvisor. (2021). About TripAdvisor.):

- *Item popularity:* A RS for a popular e-commerce platform, such as Amazon, will almost certainly have a large number of comments for popular products. A popular book, for example, may have thousands of reviews, comments, and ratings, whereas a less popular product may have only a few comments.
- *Number of users:* The quantity of users in a RS also affects the number of comments. In general, a system with a large user base will have more comments than one with a small user base.
- *The frequency of recommendations:* This can also have an effect on the number of comments. As an example, consider a RS that provides daily recommendations.
- *User interface design:* The number of comments can also be influenced by the design of the user interface. For example, if the system allows users to easily leave comments and feedback, it is likely to receive more comments than one with a complicated or difficult – to- use interface.

Here are two examples of platforms that utilize RSs. Netflix is a well-known video streaming platform that offers personalized recommendations to its users. Through its RS, Netflix suggests movies and TV shows based on users' viewing history, ratings, and preferences. Users have the option to review and comment on the media they've viewed, which helps to enhance suggestions for the future. This system enables Netflix to cater to individual tastes and interests. For instance, a highly popular TV show like "Stranger Things" may accumulate thousands of comments and ratings, while a less popular movie might receive only a few. (Source: Netflix. (2021). How Netflix Recommendations Work.) TripAdvisor is a travel website that assists users in finding suitable hotels, restaurants, and activities for their trips. It utilizes a RS to provide personalized recommendations based on users' preferences, search history, and reviews. Users can share their experiences by leaving comments and reviews on places they have visited, helping other users make informed decisions. Well-established hotels in popular tourist destinations often have a significant number of reviews, ranging from hundreds to thousands, whereas less popular restaurants in less frequented areas may only have a few comments available. (TripAdvisor. (2021). About TripAdvisor.)

In summary, the number of comments in a RS can vary greatly depending on factors such as item popularity, number of users, frequency of recommendations, and user interface design. While the number of comments can provide useful information, it should not be the only metric used to assess the efficiency of a RS.

2.3.3. Influencer / Celebrity / Expert Reviews

With the development of technology, new communication channels have emerged. Because of this, businesses' marketing techniques have changed as a result of the quick flow of information. Now, traditional marketing methods are insufficient in the digital age, and marketers have focused on developing strategies that can direct the consumer to purchasing behavior in the ever-developing digital environment. While creating these strategies, they carried WOM to social media, taking into account internet-based technologies, social blogs and online target audience communication. The use of individuals with a sizable following on social media sites like Instagram, Twitter, or personal blogs by businesses is known as influencer marketing. According to De

Veirman et al. (2017), marketing managers who wish to promote their goods or services or influence consumers' purchase decisions use the phenomenon of influencer marketing to harness the power of word-of-mouth (WOM). The important point in this method is that the views that the phenomena make to their followers through their posts contain sincerity and give confidence (Grafström et al., 2018). In addition, face-to-face word-of-mouth marketing provides access to other people's opinions about the product or service on social networks. It is a new strategy of the digital environment that allows consumers to collect information in different ways from different sources with which they do not have face-to-face communication.

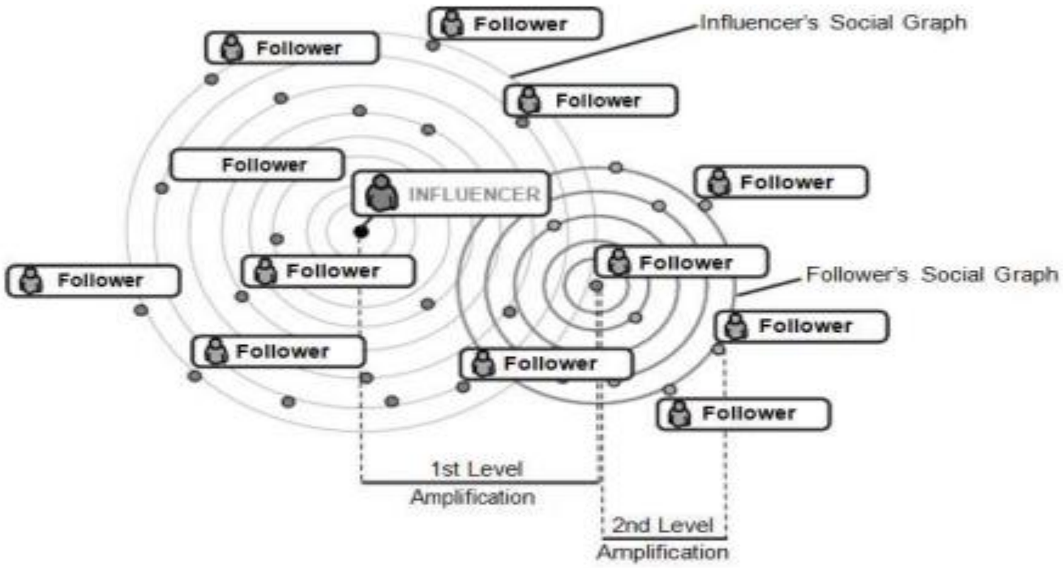


Figure 3. Fisherman’s Influencer Marketing Model (Source: Brown and Fiorella, 2013)

This model is primarily intended to "spread the widest net to catch the most fish.". The application of this is to prefer the influencers with the largest number of followers and to create the greatest brand awareness and ultimately the purchase behavior. Influencers disseminate the brand's messages or suggestions to a wide audience and allow large audiences to share them with their social circle (Brown and Fiorella, 2013). As seen in Figure 3, marketing managers choose influencers who can represent themselves and promote their products or services to large audiences (Brown and Fiorella, 2013). Influencers are phenomenal in different fields. While determining the influencers to cooperate with, institutions take into account that they are related to the brand or product, as well as that these people have a good image in the society. Celebrities / influencers, who reflect the values of the society they live in, also have a significant power in directing individuals in various ways and persuading them on any subject (Kim et al., 2014). For instance, while the work of a sportswear brand, which cooperates with a celebrity football player with a large following, is a good choice both in influencing the masses and in identifying the product with the influencer, the person with poor communication with individuals and negative news about it can damage the brand. Influencer marketing can make practitioners successful if the right phenomena are selected and well planned. For this, it is necessary to determine the communication between phenomenal people and their followers, and to measure the purchasing power of the product or brand of the followers. At the same time, in which social media tool and what type of sharing will be more effective, it should be determined as a result of deep measurements.

As a result of the rapid growth of this industry, the online comments made by celebrities / influencers have a great impact on consumers. For instance, research have shown that expert evaluation is one of the crucial aspects influencing a consumer's buying decision, according to Maity's (2014) study. According to Wang et al. (2020), when only human experts provided negative ratings, users were more likely to be swayed by ingroup members (as opposed to unidentifiable members). This was also true when only human experts provided good reviews. In the study conducted by Feng et al. (2021), the persuasion process of social media influencer marketing on consumers is mentioned.

CHAPTER 3: THEORETICAL BACKGROUND

3.1. Theoretical Background

The functioning of the human mind has been a matter of curiosity for centuries. In the early 1900s, learning processes were tried to be explained with behavioral Unconditioned stimulus, Conditioned stimulus, and Response (U-T-P) approaches, and it was attempted to be explained by the studies of Watson, Pavlov, and Skinner. In the 1940s, studies focused on the concepts of cognitive learning, perception and memory. Especially with the use of computers in the 1960s, comparisons and simulations were made between the human mind and computers, and then the "Information Processing Model", which is still accepted today, was put forward by Atkinson and Shiffrin (1968).

This theory is founded on the idea that computers and humans both use information processing to some extent. George A. Miller (1956), who developed the theory of information processing, thought that the mind perceives and processes external stimuli in order, records, accumulates and then responds to them. According to Miller, learning is the process of changing information stored in the memory (Solso et al., 2007).

3.2. Computer Metaphor

Clocks and automatons are metaphors for the 17th century mechanical worldview (Schultz and Schultz, 2007). These mechanics were easily obtainable and easily understandable models. Today, the mechanical universe view and the behavioral psychology derived from it have been replaced by the new perspective in physics and the cognitive movement in psychology. In the 20th century, when computers were developed, clocks and automatons lost their metaphorical features regarding the functioning of the human mind. The human mind can be explained with a higher model developed by itself. Therefore, the computer has begun to be used as a model for understanding the human mind (Schultz and Schultz, 2007).

Based on the assumption that computers exhibit artificial intelligence, psychologists are increasingly using their way of working to explain mental processes. It is seen that computer programs, which are nothing but a set of commands dealing with symbols, operate similarly to the human mind, and that the mind and the computer receive and comprehend a large amount of information (stimulus or data). They process, manage, store and retrieve this information when necessary, and act on it in various ways. Therefore, programming provides an example for the cognitive process view of human knowledge (Solso et al., 2007). It is this program (not hardware, but software) that serves to explain mental processes, not the computers themselves (Solso et al., 2007; Cervone and Pervin, 2015).

3.3. Information Processing and Computers

The theory claims that the human mind structure is very much like a computer in terms of processing and analyzing information. In addition, before new information entering the brain is stored in memory/memory rooms, it is first analyzed and then tested over various criteria. Since these processes occur at a very high speed, it is not possible for people to notice it. Human sensory perceptions operate like a computer hardware operation. Therefore, the rules and strategies that people use during learning are similar to the software used by the computer. In this context, the human information processing system can be improved by arranging perceptions and rules. (Schunk, 2012; Cervone and Pervin, 2015).

3.4. Information Processing Model

In the information processing model, the individual is active in the learning process. The individual selectively receives not all but some of the environmental stimuli and interprets the stimuli with which he interacts. The acquisition of behaviors is the interaction of old information with new information. Thanks to old information, new stimuli can be given meaning and new information is stored by associating them with old information. The Information Processing Model explains the production of human behavior with three basic structures interacting with each other: It consists of three main components: cognitive processes, information stores and cognitive information. Information stores are memories where information is stored, including sensory memory, long-term memory and working memory. These are also the stages of the information processing process.

- *Sensory register/processing/memory:* It is the part of mental processing units that takes all information and stores it temporarily or permanently. The stimuli received from the environment primarily enter and register in the sensory memory through the sense organs. Some receptor cells in the human sense organs receive external energy and transform it into certain messages for the brain. Accurate perception of information at this stage is very important for other stages. A valid response is generated if the external stimulus has interesting properties or has activated an existing prototype. The more important, perceptible or stimulating information is, the more easily and perfectly it is perceived by the senses. The perceived raw stimuli are kept in the sensory record as raw information for a very short time. The raw information coming to the sensory memory is sent to the short-term memory through attention, perception and recognition (Woolfolk, 2016).

- *Short-term working memory / memory:* In working memory, raw information is made meaningful by thinking about it and combining it with information in long-term memory. At this stage, the raw information from the sensory register is processed. For this reason, working memory is another name for short-term memory. In the working memory, very little information (7+/-2 units, that is, at least 5, at most 9 units of information can be stored) can be kept for a time period of about 20 seconds, that is, for a very short time. Repetition processes are used to prolong the retention time of information in working memory (Woolfolk, 2016). There are two types of operations in short-term memory. One of these is the transformation of raw information into behavior (reacting to a stimulus) immediately after the raw information, and another method involves storing it in long-term memory by creating meaningful coding.
- *Long-term memory:* It is the repository where information is constantly stored. Unknown is the size of long-term memory. Information can be kept here until it is needed for a long time, it is called from here when needed and then sent here again with new variants. In long-term memory, information is stored in different parts according to its characteristics: semantic memory (memories), memory (theoretical-theoretical information) and procedural memory (methods of doing a job) (Woolfolk, 2016).

Cognitive processes are mental activities that enable the transfer of information from one memory to another. These are attention, perception, repetition, encoding, and retrieval. In learning with the information processing process, the information desired to be learned is noticed and selected among other raw sages through attention as a stimulus or raw information. Then the stimulus or raw information is transformed into meaningful information by perception. While the information that is wanted to be stored continuously is transferred from the working memory to the long-term memory, the information is stored in the long-term memory with the repetition process, the coding process in which the mental symbols of the information are created (Woolfolk, 2016). Retrieval, which is the last of the cognitive processes, is the search for information stored in long-term memory and transferring it to the working / short memory for use. The retrieval process is impacted by the coding format used when information is moved from working memory to long-term memory. It might be simpler to obtain meaningful coded information (Woolfolk, 2016).

Cognitive information fulfills the task of ensuring that information stores and cognitive processes operate in an integrated manner in the information processing process. Cognitive knowledge is subjective, that is, it is related to the individual himself. The individual controls and directs the cognitive processes called attention, perception, repetition, encoding and retrieval with his cognitive knowledge (Woolfolk, 2016).

In the field of e-commerce, this theory investigates how the type of meaning and type of significance presented in e-commerce offers shapes the consumer's interest in product attribute information (Trzebiński and Marciniak, 2022), how information about sellers' profiles affects buyers' decision-making process, and how the stake of a transaction interacts with sellers' profile in influencing purchases (Dai et al., 2018) were used to examine.

3.5. Relationship between RSs and IPT

The connection between RSs and IPT can be seen in how RSs rely upon cognitive processes, as defined by the IPT, to create tailored recommendations to users. These systems are programmed to evaluate large amounts of user data including likes, behavior, and feedback, and then use algorithms to sift through the information and generate suggestions. These algorithms often utilize processes such as perception, attention, memory, and decision-making which are integral to the IPT (Resnick and Varian, 1997)

Perceiving user preferences and interests is a key component of RSs. Attention is given to items that are most relevant to the user, while memory is used to store and access historical data from past interactions. Decision-making then utilized to produce recommendations due to the analyzed data and algorithms, and these are then presented to the user for them to make their own decisions (Zhang and Hurley, 2010; Konstan et al., 2012).

The IPT focuses on the role of the user in taking in and interpreting information, and RSs look to make this process easier by providing tailored recommendations that fit the user's cognitive abilities and tastes, thus improving their decision-making and the general user experience (Ricci et al., 2015).

3.6. IPT in E-Commerce Industry

The Information Processing Theory focuses on how people mentally process information. This theory includes four basic components of the human mind: sensory memory, long-term memory, working memory, and decision-making. Individuals begin the process of processing information that they perceive in their sensory memory, and this information is temporarily stored in their working memory. It is utilized to store learnt knowledge for the long-term and is a more durable sort of memory. Finally, according to Huang and Hsieh (2016), the decision-making process is the act of choosing a course of action based on the knowledge at hand.

Studies conducted in the e-commerce field have been designed based on the IPT. These studies focus on understanding the information processing processes of consumers on e-commerce websites and are designed to optimize these processes. For example, product pages on e-commerce sites are visually designed to attract consumers' attention in their sensory memory. Additionally, important information such as product features and prices are emphasized to help consumers retain information in their working memory for a longer period of time (Seitz and Kim, 2021).

Long-term memory includes consumers' past experiences and purchasing habits on e-commerce sites. This information can be used through personalized recommendations and advertisements. The decision-making process of consumers is also designed on e-commerce sites. For instance, product comparison features or other consumer reviews can assist consumers in their decision-making process (Huang and Hsieh, 2016).

The IPT can be used to understand and optimize consumer behavior in the e-commerce field. The design of e-commerce sites should take into consideration consumers' information processing processes in their minds.

Several studies conducted in the e-commerce field have utilized the IPT as a framework. For example, Huang and Li (2017) investigated the impact of visual and social cues on purchase behavior in social commerce. Wang and Emurian (2005) explored the concept of online trust and its influence on consumers' information processing and purchase behavior. Zhou and Lu (2011) examined mobile instant messaging user loyalty by considering network externalities and flow experience. In addition, Liang and Huang (1998) used a transaction cost model to conduct a study on consumers' acceptance of goods in electronic markets. These studies demonstrate the application of the IPT in various aspects of e-commerce research. These studies provide examples of how the IPT is applied in the e-commerce field and offer useful guidance for the design and operation of e-commerce sites.

CHAPTER 4: METHODOLOGY

3.1. Research Development

3.1.1 Mixed method

In the late 1980s and early 1990s, the mixed method—a relatively recent research methodology—started to take shape (Creswell and Creswell, 2017; Creswell and Poth, 2016). This approach has gone through many stages of development, from formulation to intellectual discussion, procedural innovation and expansion, and has spread to many disciplines and countries around the world (Creswell, 2017). After the qualitative method and the quantitative method, the mixed method is accepted as the third major research method by many researchers (Teddlie and Tashakkori, 2012; Creswell and Poth, 2016; Johnson and Christensen, 2019). There are many common terms for this approach, such as synthesis, qualitative and quantitative approach, integration and multiple method, but recent publications use the term "mixed method" (Creswell and Poth, 2016).

Many definitions of the mixed method have been made in the literature. For example, Teddlie and Tashakkori (2012) defined it as “a type of research design in which qualitative and quantitative approaches are used in question types, research methods, data collection and analysis procedures, and/or inferences”, and Johnson and Christensen (2019) defined it as "... a category of research in which the researcher mixes or combines qualitative and quantitative research techniques, methods, approaches, concepts, or language in a single study", Creswell and Creswell (2017) defined this as "...a researcher in a single study or “research in which the research program collects and analyzes data, integrates findings, and draws conclusions using both qualitative and quantitative methods”.

Following consultation with 19 experts in the field of mixed methods, Johnson and Christensen (2019) offered the following basic and extensive explanation of this methodology: "A type of research in which a researcher or team of researchers combines elements" is defined as "qualitative and quantitative research approaches (e.g., qualitative and quantitative perspectives) for the breadth and depth of mixed methods research, understanding and support, use, data collection, analysis, and inference techniques." A further finding by Johnson and Christensen (2019) was that:

- The mixed method is the third research paradigm in the literature.
- The mixed method is the result of integrating quantitative and qualitative research approaches on an intellectual and practical level.
- The mixed method offers a robust paradigm choice that produces the most complete, balanced, informative and useful research results.

The values and motivations that push academics to use mixed methods in their studies have been determined as follows:

- A very powerful method is the mixed method because it combines the advantages of both quantitative and qualitative methods and helps researchers answer both confirmatory and exploratory questions simultaneously (Creswell and Creswell, 2017; Teddlie and Tashakkori, 2012).
- The use of this methodology leads to a comprehensive explanation of the research questions (Teddlie and Tashakkori, 2012; Creswell and Poth, 2016; Johnson and Christensen, 2019), as the observations and conclusions reached using this approach tend to be more informative, more valuable, deeper and more useful.

Mixed methods research can be conducted for various purposes such as (Johnson and Christensen, 2019):

- *Triangulation (triangulation) research:* The purpose of this research is mostly to reach the convergence and validation of the results by using different methods and designs examining the same phenomenon.
- *Complementary research:* This research designed to explain, demonstrate, refine and clarify the findings of one method based on the results of another method.
- *Initial research:* This research aims to explore the paradoxes and contradictions that contribute to the reformulation of the research question.
- *Improvement research:* The findings of one method are used to better guide the other method.
- *Extension research:* By utilizing several approaches for distinct study components, it aims to increase the breadth and depth of research.

In general, there are different methods of data collection. The main instruments used in mixed methods research are, interviews, classroom observations, and lastly, closed and open-ended questionnaires. The validity and reliability of the data can be increased by combining these various forms of data collection. In general, closed-ended questionnaires are used to get quantitative data, whereas open-ended ones, interviews, and classroom observations are used to gather qualitative data (Creswell and Creswell, 2017). The key study objectives and research questions are used to construct the questionnaire items. For this study, we employ interviews, one of the qualitative research methodologies, as the initial step in the research process.

The qualitative research method, which is popular notably in the field of social sciences, was employed in our study. A widespread definition of qualitative research that is accepted by everyone cannot be made. The main reason for this situation is the use of the concept of qualitative research as an "umbrella concept". Many concepts that are likely to be included under this umbrella are closely related to different disciplines. Anthropology, situational research, interpretive research, etc. since the research patterns and analysis techniques of many concepts have similar structures with each other, "qualitative research" is accepted as a general concept covering these concepts. For this reason, most authors in the literature avoid making a definition on this subject (Yıldırım, 1999).

Creswell and Creswell (2017) state that the use of interpretative or theoretical frameworks in qualitative research is the first step. These frameworks address the meanings that individuals or groups attribute to social or humanitarian situations through presumptions and contain a thorough analysis of study topics. In order to investigate the problem, he uses a qualitative approach that includes data collections in the natural environment sensitive to people and places, both inductive and deductive, data analysis that establishes patterns and themes in the research. The final result, on the other hand, includes the voices of the participants, the deep thoughts of the researcher, a complex explanation and interpretation of the problem, his contribution to the literature or a call for change. Another definition of qualitative study includes observations, interviews, and document analysis, as well as the use of qualitative data collection techniques, perceptions, and events in their natural environments (Yıldırım, 1999). This definition was used to gain a holistic understanding of a process.

Qualitative studies are carried out because a problem or topic needs to be explored. This discovery, on the other hand, arises from the need to study a group or the universe, to identify variables that cannot be easily measured. This is the best reason to explore a problem instead of using the information already determined in the literature or relying on other research results. Qualitative research is carried out to bring a more detailed understanding to a complex issue (Creswell and Poth, 2016).

In the studies related to qualitative approaches, the study's procedures necessarily involve the researcher. Researchers always use their own intellectual knowledge to make sense of and interpret the data they obtain. For this reason, reality is multiple and subjective in nature in qualitative studies (Salvador, 2016).

Working qualitatively necessitates a strong commitment to solving the situation at hand as well as the necessary time and resources. It should not be viewed as a straightforward substitute for quantitative research because it is associated with the most rigorous quantitative approaches. In a qualitative study, a researcher spends hours in the field, collects extensive and comprehensive data, examines the problems of the field in order to gain access, proximity and an insider's perspective. Creswell and Poth (2016) engaged in a complex and time-consuming analysis process, extracting the data he has obtained in large quantities and reducing the data to several themes or categories. In order for the findings to prove the claims and because the author needs to show different points of view, he writes long passages and gives plenty of quotations to reveal the points of view of the participants (Creswell and Poth, 2016).

Qualitative studies are verbal-weighted and interpretation-based studies that are widely used in social research and deal with attitudes, behaviors and experiences. Case studies, action studies, culture analysis, feminism studies, and embedded theory are a few examples of these studies. It fits into the following categories (Padem et al., 2012). After the participants are interviewed, the DCE survey started.

3.1.2. Determination of Variables

The attributes and levels were refined using a variety of approaches. They were based on the best practice guidelines (Bridges et al., 2011; Johnson et al., 2013; Helter and Boehler, 2016; Barber et al., 2019; Sever et al., 2019; Janssen et al., 2016). First of all, a thorough list of qualities and levels was discovered after conducting a literature review (Table 1).

Table 1. Attributes of DCE according to the literature

ATTRIBUTES (ACCORDING TO THE LITERATURE)	**REFERENCES**
Type of comments	Thurau and Walsh, 2003; Thurau et al., 2004; Chevalier and Mayzlin, 2006; Park et al., 2007; Sen and Lerman, 2007; Park and Lee, 2009; Sparks and Browning, 2011; Almana and Mirza, 2013; Baum and Spann, 2014; Ventre and Kolbe, 2020; Kripesh et al., 2020; Yuan et al., 2020; Vermaand Yadav, 2021; Pyle et al., 2021; Alwan and Alshurideh, 2022
Number of comments	Herlocker et al., 2000; Dellarocas, 2003; Godes and Mayzlin, 2004; Liu, 2006; Chevalier and Mayzlin, 2006; Hu et al., 2008; Forman and Ghose, 2008; Lee et al., 2008; Zhu and Zhang, 2010; Ghose and Ipeirotis, 2011; Chen et al., 2011; Tintarev and Masthoff, 2012; Tintarev and Masthoff, 2012; Filieri and McLeay 2013; Zhang et al., 2015; Huang and Chen, 2017; Xie et al., 2017; Netflix. (2021). How Netflix Recommendations Work; TripAdvisor. (2021). About TripAdvisor

Table 1 (Cont'd). Attributes of DCE according to the literature

Type of ratings	Thurau and Walsh, 2003; Thurau et al., 2004; Chevalier and Mayzlin, 2006; Park et al., 2007; Sen and Lerman, 2007; Park and Lee, 2009; Sparks and Browning, 2011; Almana and Mirza, 2013; Baum and Spann, 2014; Ventre and Kolbe, 2020; Kripesh et al., 2020; Yuan et al., 2020; Verma and Yadav, 2021; Pyle et al., 2021; Alwan and Alshurideh, 2022
Number of ratings	Herlocker et al., 2000; Dellarocas, 2003; Godes and Mayzlin, 2004; Liu, 2006; Chevalier and Mayzlin, 2006; Hu et al., 2008; Forman and Ghose, 2008; Lee et al., 2008; Zhu and Zhang, 2010; Ghose and Ipeirotis, 2011; Chen et al., 2011; Tintarev and Masthoff, 2012; Tintarev and Masthoff, 2012; Filieri and McLeay 2013; Zhang et al., 2015; Huang and Chen, 2017; Xie et al., 2017; Netflix. (2021). How Netflix Recommendations Work; TripAdvisor. (2021). About TripAdvisor
Influencer/Expert/ Celebrity comment	Brown and Fiorella, 2013; Kim et al., 2014; Maity, 2014; De Veirman et al., 2017; Grafström et al., 2018; Feng et al. 2021; Cho et al. (2018), Casaló et al. (2018), Balabanis and Diamantopoulos (2016), Chen et al. (2020), and Hosseini et al. (2020)
The way the item is recommended	Deshpande and Karypis 2004; Adomavicius and Tuzhilin, 2005; Dhar and Varshney, 2011; Bell and Koren, 2007, Koren, 2010; Breese et al. 2013; McAuley et al., 2015 Wang et al., 2015

After that in the literature of DCE, qualitative studies are performed in the derivation of attributes and levels of attributes (Coast and Horrocks, 2007; de Bekker-Grob, 2009; Rao et al., 2013). DCE conducted with the subject in the study of the attributes associated with the determination of the features and levels in addition to literature review, focus group discussions or in-depth interviews are used (Kolstad, 2011; Kruk et al., 2010; Mangham and Hanson, 2008; Rockers et al., 2012).

In the light of this information, qualitative studies have been conducted in order to determine the variables used in the research, namely the most important characteristics affecting online shoppers between the ages of 18 and 65. First, an in-depth interview form (Appendix A) was prepared by conducting a literature review at the national and international levels to be used in the in-depth interviews. Between January 2021 and February 2021 interviews were conducted over the phone or in person.

In-depth interviews were conducted with 10 people with different characteristics in about 45 minutes. The details of the interviews are given in the sample table below (Table 2). In the interview conducted on a voluntary basis, a heterogeneous group was formed by selecting different people in terms of age, marital status, gender, monthly income experience. A voice recording was made during the interview by obtaining the permission of the participants. Then analyzing these interviews, the participants of which the most effective choice while shopping, the most persistent and analyzed by thematic coding method and focus on the most important variables were determined.

To reach the interviewees for the in-depth interviews, a sampling strategy was employed to ensure a diverse and representative group of participants. The sampling process involved the following steps: identifying the target population, determining the sample size, recruitment of participants, forming a heterogeneous group, obtaining informed consent, conducting the interviews, voice recording, thematic coding and analysis, and lastly, focus on important variables.

By following this sampling and interview process, this study aimed to obtain valuable and diverse insights into the shopping behavior of the participants, considering the factors that influence their choices.

Table 2. Demographic Characteristics of the Interviews

Participants	Age	Gender	Occupation	Duration of Interview
P1	18	Female	Student	32
P2	20	Male	Student	36
P3	24	Female	Psychologist	41

Table 3 (Cont'd). Demographic Characteristics of the Interviews

P4	28	Male	Engineer	35
P5	31	Male	Logistician	28
P6	36	Female	Unemployed	44
P7	44	Male	Engineer	32
P8	47	Female	Engineer	35
P9	50	Female	Teacher	40
P10	52	Female	Retired	38

The most important features that participants pay attention to in online shopping are the rating of product, number of comments, the comment with photo, the way the item is recommended and influencer comments (Table 3).

Table 4. Attributes and Pioneering Quotes of the Interviews

Attributes	Pioneering Quotes
The way the item is recommended	*'I prefer products to be recommended based on the ones I have personally examined.' (P2).* *'I would like products to be recommended based on both my own product history and the product history of other users who have viewed that product.' (P9).*
Influencer comments	*'The opinions of influencers are crucial for me. For example, I am heavily influenced by influencers who share the products they have received on social media, and I end up buying them.' (P3).*

Table 5 (Cont'd). Attributes and Pioneering Quotes of the Interviews

The rating of product	*'The product needs to have at least 4 stars; I don't consider any product with less than 4 stars.' (P1).* *'If a product has a star rating of 1, I don't consider that product.' (P6).* *'The product needs to receive at least 4 stars.' (P10).* *'When buying a tech device, the star rating greatly influences my purchase decision. In general, I rely on the star rating and can alter my decision accordingly.' (P5)*
Number of comments	*'I pay attention to the number of comments in my shopping.' (P4).* *'If there are many comments, it influences my purchase decision positively.' (P7).* *'The number of comments is important to me. If a product has received too many negative comments, I refrain from purchasing that product.' (P10)*
The comment with photo	*'If a comment with a photo is posted, I find that comment trustworthy.' (P1).* *'In the past, the reliability of comments used to be debated, but now we have photo comments.' (P8).*

The features and sub-levels of online shopping that will be used in the preparation of scenarios in the research that will be conducted based on the literature review and in-depth interviews based on DCE are presented in Table 1. Five variables were determined as the way the items were recommended (2 levels), the number of comments (3 levels), the influencer comment (2 levels), the comment with photo (2 levels) and the rating of product (3 levels) (Table 4).

Recommending products to other users based on a user's product history on online marketplaces can provide benefits such as increasing cross-selling and improving consumer satisfaction. Studies in this field generally involve topics including data mining, machine learning, and artificial intelligence. Examples of studies on recommending a product to other users based on their product history in e-commerce include Deshpande and Karypis (2004), Adomavicius and Tuzhilin (2005) and Wang et al. (2015).

To provide recommendations to consumers on online marketplaces, it may be necessary to analyze their previous purchase history and use that data. Examples of such studies include Dhar and Varshney (2011), Bell and Koren (2007), Koren (2010), McAuley et al. (2015), and Breese et al. (2013).

In Forman and Ghose (2008), Huang and Chen (2017), Lee et al. (2008), Liu (2006), and Zhu and Zhang (2010) studies, it is observed that when a product receives less than 50 comment, the scarcity of reviews could negatively affect consumers' purchasing decisions and may decrease sales.

Chen et al. (2011), Filieri and McLeay (2013), Ghose and Ipeirotis (2011), Hu et al. (2008), and Zhang et al. (2015) studies investigate the impact of products receiving between 50 and 100 comments on consumers' purchasing decisions. Observations show that comments within this range can have an impact on consumer buying behavior and boost sales.

In Godes and Mayzlin (2004), Dellarocas (2003), Xie et al. (2017), Chevalier and Mayzlin (2006) and Chen et al. (2011) studies, it is observed that when a product receives more than 100 comments, these reviews have a bigger effect on consumers' buying choices and boost sales.

Cho et al. (2018), Casaló et al. (2018), Balabanis and Diamantopoulos (2016), Chen et al. (2020), and Hosseini et al. (2020) examine influential comments' effects on variables like purchase intention, consumer attitude, and social commerce experience in e-commerce.

Chatterjee and Hoffman (2018), Duffett (2015), Lee and Kim (2018), Sundaram et al. (1998), and Yang and Mai (2018) analyze how photo comments affect consumer traits including purchase intent, trust, and contentment.

The studies related to a product receiving a rating of 4.5 or higher on online marketplaces are Anderson et al. (1994), Zhu and Zhang (2010), Dellarocas (2003) and Chevalier and Mayzlin (2006).

Chen et al. (2011), Chevalier and Mayzlin (2006), Liu (2006), Dellarocas (2003), and Zhu and Zhang (2010) have conducted studies on online marketplaces regarding a product receiving a rating above 3.5 and below 4.49.

Studies by Karakaya and Aydın (2019), Ye et al. (2009), Chen et al. (2011), and Moe and Trusov (2011) have investigated the relationship between a product receiving a rating between 2.5 and 3.49 and its impact on sales.

Table 6. Attributes with Levels

ATTRIBUTES	**LEVELS**
The way the item is recommended	According to my own product history
	According to the product history of other users
Number of comments	0 - 49
	50 - 99
	100+
Influencer comments	Yes
	No
The comment with photo	Yes
	No
The rating of product	Above 4.5
	3.5 – 4.49
	2.5 – 3.49

3.2. Pilot Test

Prior to doing research or an experiment, a pilot test is used. Before analyzing the data, it can give researchers crucial information, and it can also aid to improve the results' correctness. Its significance has the potential to raise the standard of the research and improve the precision of the findings (Fraenkel et al., 2018).

Firstly, in theoretical research, it can help to evaluate the accuracy of data collection methods and research questions. Researchers can test the validity and reliability of the surveys, interviews or other data collection tools they will use in their research. This can improve the structure of the research and make the results more precise (Johnson and Christensen, 2019). The examples and studies within the book by Johnson and Christensen (2019) discuss the general principles and approaches of various pilot tests or research. Second, it can assist researchers in comprehending how participants interact with the data and how data collecting proceeds. This enables researchers to find a more suitable method or methods to analyze the data. For example, during a pilot test, researchers can determine how to encourage more accurate responses to a particular question on a survey if preferred options are not provided (Tavakol and Dennick, 2011). Finally, it can help researchers interpret their results more accurately. The data obtained during pre-testing can help researchers determine how to analyze and interpret the results. This can ensure that the results are interpreted correctly and can help researchers make accurate decisions based on the results (DeVellis, 2017).

In practical research, Liang et al. (2018) examine what influences social commerce, which refers to users' purchasing behavior of products or services through social media platforms. In doing so, they conducted a pilot test with a sample of 60 individuals, which was carried out on an internet website. Lv and Liu (2022) examine the impact of information overload on consumer return intentions in e-commerce platforms. To check the validity and reliability of the questionnaire, a small-scale pilot test was done. For the pilot test, 197 valid questionnaires were gathered in order to examine the validity and reliability of the original survey. The influence of various social support and social commerce constructions on social commerce intentions is studied by Sheikh et al. (2019). A pilot test was carried out to make sure that the participants could clearly understand the statements of the items. 45 people participated in the pilot experiment.

In this study, for the first stage of proper analysis, which is the pilot test, we asked participants to complete the survey while considering that they were doing wallet shopping from online marketplaces. the pilot test included 50 participants between the ages of 18 and 65, who worked in various sectors or were students and lives in Izmir / Türkiye. Pilot test survey is in the Appendix B.

JMP Pro 16.0.0, statistical software, was used to evaluate the pilot test results, and the following outcomes were obtained to be used for the main test (Table 5).

Table 7. Analysis of the Pilot Test

Term	**Estimate**	**Std Error**	**Variance**
The way the item is recommended [According to my own product history]	0,554	0,0222522	0,00049516
The way the item is recommended [According to the product history of other users]	0,446	0,0222522	0,00049516
Number of comments [0 - 49]	0,172	0,0168939	0,000285404
Number of comments [50 - 99]	0,512	0,0223766	0,000500712
Number of comments [100 +]	0,316	0,0208124	0,000433156
Influencer comments [Exist]	0,658	0,0212361	0,000450972
Influencer comments [Not exist]	0,342	0,0212361	0,000450972
The comment with photo [Exist]	0,770	0,0188391	0,000354912
The comment with photo [Not exist]	0,230	0,0188391	0,000354912
The rating of product [2.5 - 3.4]	0,034	0,0081129	0,000065
The rating of product [3.5 - 4.4]	0,526	0,0223528	0,000499648
The rating of product [Above 4.5]	0,440	0,0222213	0,000493786

After analyzing the pilot test, the obtained values were entered into JMP Pro 16.0.0. Statistical Software to determine the scenarios for the main test. The Estimate values were entered as Prior Mean, and the Variance values were entered into the Prior Variance Matrix (Appendix C). Based on this information, the main test survey was generated (Appendix D).

In conclusion, it can help researchers understand and analyze data more effectively. This can enhance the quality of research and ensure that the results are more accurate. Therefore, the importance of it is significant in the research process.

3.3. Main Test

The main test is a crucial tool used in the design of a research study that follows the pre-test phase. The purpose of this test is to assess the results and determine whether the hypotheses that were formed based on the pilot-test results were valid. The main test allows researchers to solve any problems identified during the pre-test and to conduct the research on a larger sample (Creswell and Creswell, 2017).

The main test's significance resides in its capacity to assure the reliability and validity of the research findings. By testing the hypotheses established during the pre-test, the main test determines whether the research has achieved its objectives. The results of the main test provide important information to researchers to progress with their research and to plan future studies (Sekaran and Bougie, 2016).

Proper planning and management are required to conduct the main test effectively, including selecting the appropriate sample, collecting data accurately, and analyzing the data using statistical and analytical techniques. The analysis of the results obtained from the main test helps researchers understand the significance of the data collected and determine the implications of the results (Trochim and Donnelly, 2008).

In conclusion, the main test is an important tool used to determine the success of a research study and to analyze its results. Its correct implementation is critical for ensuring the validity and reliability of the research results.

3.3.2. Sampling

The method known as a DCE involves having consumers select amongst a variety of options for goods or services that each have unique qualities. This method can also be used in studies conducted on online marketplaces (Lancsar and Louviere, 2008).

In DCE studies, participants are usually selected using random sampling. These participants may have predetermined characteristics or may be selected as representatives of a particular target audience. In online marketplaces, for example, consumers on an e-commerce site can form a potential sample for these studies (Ryan et al., 2008).

The sample size may vary depending on the objectives and analyses of the DCE study. It is important to have a sufficient number of participants for generalizations to be made. When determining sample size, factors such as the aim of the study, the sampling method, and the product or service category may be taken into account (Ryan et al., 2008).

In DCE studies, a set of product or service options with specific characteristics is presented to each participant to allow their choices to be statistically analyzed. Participants answer a series of questions to determine their preferred options. After the data is collected, statistical analyses can be used to determine how participants' choices were influenced and which characteristics had the greatest impact on their preferences (Hensher et al., 2005).

As a result, in DCE studies conducted on online marketplaces, a specific sample can be selected using random sampling and a set of product or service options can be presented to this sample. The collected data can be evaluated using statistical analyses, and the results can be useful for product or service development or marketing strategies (Hensher et al., 2005). In this study, for sampling, participants should be between 18-65 years old and have experience in online shopping. Because convenience sampling was used in this study, and all participants were required to have online shopping experience. Convenience sampling is a method used by researchers to sample participants who are easily accessible and available (Bhardwaj 2019). This method involves selecting individuals or groups that the researcher can easily reach from a specific population (Bhardwaj 2019). It is an important sampling method to be cautious about when making generalizations, as the obtained results may not represent the entire population (Bhardwaj 2019).

3.3.3. Data Collection

During the data collection survey, 621 people were contacted via online channels. Out of the 621 respondents, 500 were considered as the final valid sample for the study. A screening question was also included to make sure that respondents have experience shopping online. The frequency of the participants' gender, age, income, marital status, degree of education, and employment was assessed using IBM SPSS Statistics 23 (Table 6). This was written to give a broad summary of the fundamental traits of survey respondents. The definition of online shopping and details of online marketplaces were clearly defined.

Table 8. Demographic Characteristics of the DCE Sample

Characteristic	Frequency	Percentage
Gender:		
Female	241	48.2
Male	259	51.8
Total	500	100
Age:		
18-25 years old	186	37.2
26-35 years old	300	60.0
36-45 years old	6	1.2
46-55 years old	8	1.6
Age 56 or older	0	0.0
Total	500	100
Marital status:		
Married	147	29.4
Single	353	70.6
Total	500	100
Education level:		
Primary-secondary school	1	0.2
High school	52	10.4
Bachelor’s degree or higher	447	89.4
Total	500	100
Education level:		
Primary-secondary school	1	0.2
High school	52	10.4

Table 6. (Cont'd). Demographic Characteristics of the DCE Sample

Bachelor's degree or higher	447	89.4
Total	500	100
Income:		
8500 TL- 13500 TL	7	1.4
13501 TL- 18500 TL	10	2.0
18501 TL- 23000 TL	22	4.4
23001 TL- Above	461	92.2
Total	500	100
Occupation:		
Employeed	336	67.2
Retired	3	0.6
Unemployed	12	2.4
Student	149	29.8
Total	500	100

48.2% of respondents (n = 241) were female, and 51.8% (n = 259) were male, as seen in the demographics table above. Among the responders, the ages of 37.2% (n = 186), 60.0% (n = 300), 1.2% (n = 6) and 1.6% (n = 8) were 18 to 25, 26 to 35, 36 to 45, and 46 to 55, respectively. When the marital status was taken into account, 29,4% (n = 147) of respondents were married, while 70,6% (n = 353) were single. In addition, the vast majority of respondents (n = 447) had a bachelor's degree or higher, representing 89,4% of their educational background. High school attendance was 10,4% (n = 52) while primary-secondary attendance was 0,2% (n = 1).

Additionally, the respondents' yearly income played a key role in classifying them according to their level of income. 1,4% (n = 7) of the respondents reported monthly incomes between 8,500 and 13,500 TL. 2,0% of respondents (n = 10) had a monthly income of between 13501 TL and 18500 TL. 4,4% (n = 22) of those surveyed made between 18501 and 23,000 Turkish Liras every month. The majority of respondents (92,2%, n = 461) had monthly incomes of 23001 TL or more.

Last but not least, the study also took the respondents' professions into account. 67,2% (n = 336) of respondents reported having a job. 0.6 percent of respondents (n = 3) were retired. 29,8% (n = 149) of respondents were students, compared to 2,4% (n = 12) of respondents who were unemployed.

CHAPTER 5: ANALYSIS AND RESULTS

5.1. Pilot test

The result of the pilot test conducted in this study explained in Chapter 3.

5.2. Main Test

DCE is a widely used method to determine consumers' preferences and tendencies. Using DCE to measure the accuracy of a RS used in e-commerce is an important step. DCE enables consumers to determine their preferences by presenting them with different options, thereby helping to better understand consumer behavior (Zhen et al., 2019).

The main test is the primary application of DCE and is used to evaluate real-time responses from actual consumers. The importance of the main test includes the following:

- Realistic results: The main test reflects the preferences of real consumers in the real world, making it a valuable tool for measuring the effectiveness and accuracy of the RS on real users. The responses of real consumers allow you to obtain more realistic and reliable results about the system (Lai and Tsai, 2018).
- Discovery of preferences: The main test allows you to analyze consumers' reactions to different options. This helps you better understand consumer preferences and priorities and determine how the RS can meet those preferences. In this way, you can develop better strategies to improve the RS and enhance consumer satisfaction (Lai and Tsai, 2018).
- Validation of the RS: The main test enables you to evaluate the effectiveness and accuracy of the RS on real consumers. By measuring the actual responses of consumers, you can assess the extent to which the recommendations provided by the system meet consumer satisfaction and purchase preferences. This provides important feedback for the development and improvement of the RS (Lai and Tsai, 2018).

The main test is a critical stage in obtaining accurate results and measuring the effectiveness of a RS used in e-commerce. It serves as an important tool for validating and improving the system by reflecting real consumer responses (Zhen et al., 2019).

It is possible to measure the accuracy of a RS on a consumer basis by using Bayesian Design and DCE. Bayesian Design is a method used to test pre-defined hypotheses and can be used to make very sensitive measurements through consumer's selections of products. DCE is a method used to measure consumer's selections of products. By using Bayesian Design and DCE, the accuracy of a RS on a consumer basis can be measured and this can help brands to improve their products and RS (Sarwar et al., 2001). Therefore, Bayesian Design was used in this study.

5.2.1. Bayesian Design

DCE is a technique based on a process of making choices between alternative options that include different features and prices regarding a good or service. DCEs are used to understand consumer behavior and market preferences (Ben-Akiva et al., 2019).

Bayesian design is a method used in DCEs to optimize the features of a study (Jonker et al., 2018). This design develops an experimental plan based on specific information and aims to achieve higher accuracy with fewer trials (Jonker et al., 2018). Bayesian design optimizes factors such as sample size and data collection timing to reduce uncertainties in the data collection process trials (Jonker et al., 2018). This technique maximizes the utilization of acquired data and aids a researcher in determining how much data to gather during the data collection process (Jonker et al., 2018).

There are many studies that use Bayesian design in DCEs. For example, in a study conducted to analyze preference for health services, Bayesian DCE was used to understand patients' behavior of choosing between different medical procedures (Ryan et al., 2008). In another example, Bayesian DCE was used to understand homeowners' preferences between different energy efficiency investments to reduce energy consumption (Hynes et al., 2013).

In another study, Bayesian DCE was used to understand why consumers prefer organic foods (Schaer et al., 2012). This study took into account factors such as the price, quality, and certification of organic foods. In addition to these examples, there are many studies in tourism, environment, transportation, and other fields that use the Bayesian DCE method.

In this study, for the analysis, Bayesian Design is used. Bayesian design is a method used to determine data collection strategies during a main test. This method allows a researcher to determine which data needs to be collected in order to achieve a specific goal during data collection. In this way, researchers can increase the value of collected data and improve the accuracy of the results obtained (Berry et al., 2010).

Many studies use Bayesian design to conduct main tests. Such studies provide a method that allows researchers to reduce uncertainties in the data collection process and increase the value of collected data. Additionally, this method helps researchers to have more information about research design and improve the accuracy of the results obtained (Liu et al., 2018; Moustaki, 2020; Ranganathan and Pramesh, 2017).

In summary, Bayesian design is a method used to reduce uncertainties in the data collection process during a main test and increase the value of collected data. This method is used in many studies and helps researchers to improve the accuracy of the results obtained.

5.2.2. Bayesian design on online marketplaces

Bayesian design is a statistical method that can be used effectively in online markets. This method can be used to measure and improve the performance of a marketing campaign (Gelman et al., 1995).

Bayesian design uses Bayes' theorem to analyze data. This theorem is used to calculate the probability of a hypothesis. Bayesian design increases the reliability of test results and obtains more accurate results with the integration of new data using this theorem (Kruschke, 2015).

Bayesian design can be used in online marketing to evaluate and enhance the effectiveness of a marketing effort. To make it clear, if a company is introducing a new product, Bayesian design can be used to select the most effective marketing strategy among different options. This method can help companies make the right decisions to protect their budget and achieve better results (Li et al., 2021).

However, Bayesian design can produce incorrect results when not applied correctly. Therefore, it is important to collect accurate data and use the right analysis methods when using Bayesian design (Kruschke, 2015).

The use of Bayesian design for conducting main tests when it comes to e-commerce, it is experiencing a notable increase. Several studies serve as examples of this trend. For instance, Crockett (2015) employed Bayesian A/B testing was used to evaluate the effectiveness of different product pages and payment options on an e-commerce site. This design aimed to identify the most effective options to increase the site's conversion rates. Li et al. (2021) carried out research on Bayesian methods in e-commerce, utilizing them for consumer behavior analysis, product recommendations, and the development of improved marketing strategies. Similarly, Pyle (2018) utilized Bayesian statistical methods to assess the effectiveness of digital marketing campaigns, with the goal of optimizing targeting and achieving higher conversion rates.

These examples demonstrate that Bayesian design can be used in e-commerce for various purposes such as increasing conversion rates, analyzing consumer behavior, and developing better marketing strategies.

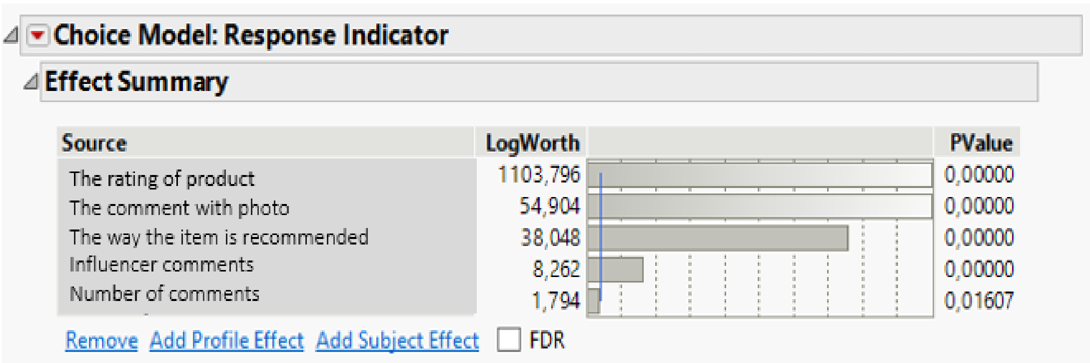
5.3. Results of Main Test

The main test survey was conducted based on the data obtained from the pilot test, which is detailed in Appendix D. To achieve this, five different surveys were prepared, each intended to have 100 participants, as outlined in Appendix C. Similar to the pilot test, The participants were told to imagine themselves shopping on internet marketplaces.

The survey was distributed to 621 participants through digital channels, and 500 were considered as the final valid sample for the study. The collected data from the main test survey was then JMP Pro 16.0.0 Statistical Software was used for the analysis.

Within the JMP Pro 16.0.0 tool, Bayesian Design was employed to analyze the attributes under investigation. The results obtained from this analysis are presented in Figures 4, 5, and 6. Based on these results, among the 500 survey participants who engage in online marketplace shopping, the attribute given the highest priority is the product rating. On the other hand, the attribute with the least perceived reliability is the number of comments.

Further examination of the results for the other attributes reveals that the attribute of comments accompanied by photos holds the second-highest importance. The manner in which items are recommended ranks as the third most significant attribute, and influencer comments are identified as the fourth most important attribute (Figure 4).



Source	LogWorth	PValue
The rating of product	1103,796	0,00000
The comment with photo	54,904	0,00000
The way the item is recommended	38,048	0,00000
Influencer comments	8,262	0,00000
Number of comments	1,794	0,01607

Figure 4. Results of the Main Test Survey

By conducting the main test survey and analyzing the data using JMP Pro 16.0.0, valuable insights have been gained regarding the attributes considered important by the 500 participants who partook in the survey and engage in online marketplace shopping.

Parameter estimates are known as 'Utility,' representing the degree of contentment that consumers derive from products possessing specific attributes (Lifke and Syroid, 2016). The Utility Profiler visually illustrates this data (Figure 5). Participants considered recommendations based on their own product history the most, which is the first attribute. The preferences of participants for the number of comments did not show much variation. The presence of an influencer comments and a comment with photos influenced participants more. Lastly, it was very important for participants that a product receives a rating of 4.5 or higher.

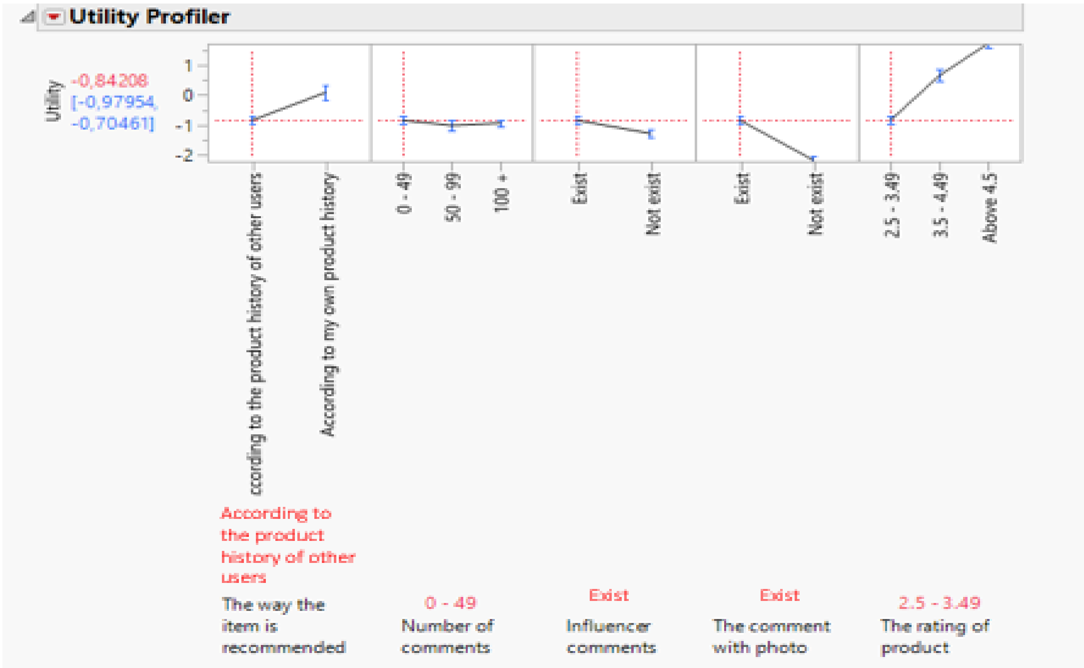
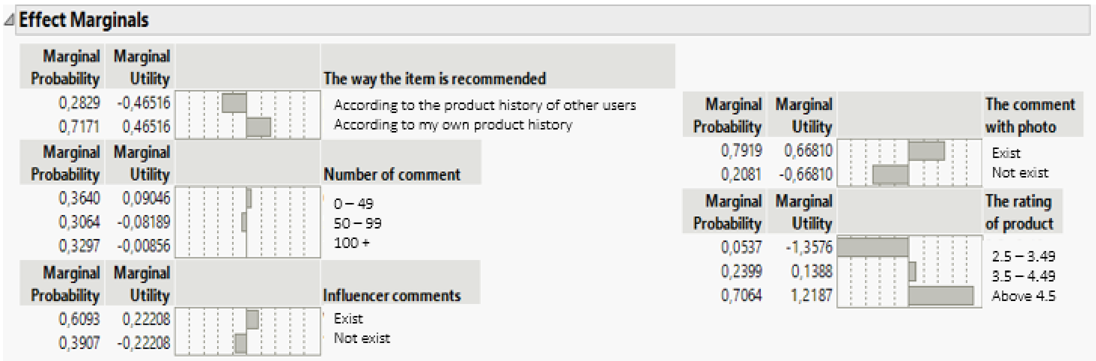


Figure 5. Utility Profiler of the Main Test Survey

Marginal utility estimates demonstrate the preference participants associate with levels of attributes (Giubilini and Minerva, 2019). The highest marginal utility estimates, indicating the strongest preference for each attribute, are listed in Figure 6.



Marginal Probability	Marginal Utility	The way the item is recommended
0,2829	-0,46516	According to the product history of other users
0,7171	0,46516	According to my own product history

Marginal Probability	Marginal Utility	Number of comment
0,3640	0,09046	0 – 49
0,3064	-0,08189	50 – 99
0,3297	-0,00856	100 +

Marginal Probability	Marginal Utility	Influencer comments
0,6093	0,22208	Exist
0,3907	-0,22208	Not exist

Marginal Probability	Marginal Utility	The comment with photo
0,7919	0,66810	Exist
0,2081	-0,66810	Not exist

Marginal Probability	Marginal Utility	The rating of product
0,0537	-1,3576	2.5 – 3.49
0,2399	0,1388	3.5 – 4.49
0,7064	1,2187	Above 4.5

Figure 6. Effect Marginals of the Main Test Survey

CHAPTER 6: DISCUSSION AND IMPLICATIONS

5.1. Discussion

The results of this study suggest that the most important factor for online shoppers when it comes to choosing products is the rating of the product, followed by the comments with photos, the way the product is recommended, influencer comments and the number of comments. These findings highlight the significance of social proof and user-generated content in influencing purchase decisions. The emphasis placed on product ratings indicates that consumers rely heavily on the experiences and opinions of others when evaluating the quality and suitability of a product. Positive ratings provide reassurance and trust in potential buyers, making them more inclined to select a product with a higher rating.

Interestingly, the study also reveals that consumers prioritize comments with photos as an influential factor in their decision-making process. Visual content serves as compelling evidence of product quality and authenticity. Consumers can visually assess the product's appearance, features, and even its performance through images shared by other users. This aspect emphasizes the importance of encouraging consumers to provide visual feedback and leveraging such content to enhance the overall shopping experience.

Furthermore, the way a product is recommended also holds significance for online shoppers. The study indicates that the presentation and positioning of a product can influence its appeal and desirability. Businesses need to carefully curate their RSs to effectively showcase products to consumers, ensuring that the recommendations align with individual preferences and needs. This personalized approach can greatly impact consumers' purchase decisions and lead to increased satisfaction.

The inclusion of influencer comments as a factor in online shoppers' decision-making process highlights the growing influence of social media and influencer marketing. Consumers are influenced by trusted individuals who endorse products through their reviews or recommendations. Leveraging influencer partnerships can enhance brand credibility and expand reach, leading to increased consumer interest and engagement.

Overall, this study sheds light on the key factors that drive online shoppers' choices and emphasizes the importance of social proof, visual content, personalized recommendations, and influencer marketing in shaping consumer behavior in the online marketplace.

5.2. Theoretical Implications

This study has significant implications for the literature on online shopping and the use of RSs. It provides evidence that consumers prioritize the rating of a product when making a purchase decision, even if the product is more expensive than other options. These findings align with previous research that suggests consumers tend to be more inclined to purchase products with high ratings, regardless of price considerations (Kaur et al., 2017).

Additionally, this study highlights the significance of comments with photos and the way products are recommended as influential factors in purchase decisions. These findings contribute to the understanding of how user-generated content and personalized recommendations shape consumers' choices. The theoretical implications emphasize the importance of considering social factors, visual content, and recommendation algorithms in designing effective online shopping experiences.

Moreover, this study underscores the need for businesses to provide accurate and reliable information about products to consumers. By prioritizing the accuracy of ratings and ensuring the authenticity of consumer feedback, businesses can build trust and credibility, leading to enhanced consumer satisfaction and loyalty.

Also, in this study, IPT was utilized. This theory is used to explain how individuals process information and make decisions. In this study, this theory was employed to understand the characteristics of trustworthy recommendation systems and how consumers respond to these systems.

IPT examines the process by which individuals acquire, organize, process, and ultimately make decisions based on information. The focus of the study was to understand how consumers process and evaluate the information received from trustworthy recommendation systems. The theoretical aspects included how consumers process information from these systems, how they evaluate information sources, and the resulting decisions made.

IPT explains how individuals evaluate information sources and determine their reliability. The study investigated how consumers trust trustworthy recommendation systems and how the provided information from these systems affects their perception of reliability. These findings can be important in understanding consumers' trust in trustworthy recommendation systems and the reliability features these systems need to provide in order to be effective.

IPT also considers the emotional, cognitive, and behavioral experiences of individuals in the information processing process. The study examined the experiences of consumers when using trustworthy recommendation systems and how these experiences influence their attitudes towards these systems.

The study found that consumers tend to prioritize the rating of a product when making purchase decisions. This aligns with previous research indicating that consumers are more inclined to buy products with high ratings (Boz et al., 2020; Gavilan et al., 2018). The study emphasizes the significance of comments with photos and the way products are recommended in shaping consumers' choices. User-generated content and personalized recommendations play a vital role in influencing purchase decisions (Lu et al., 2020; Li et al., 2021). The study underscores the need for businesses to provide accurate and reliable information about products to consumers. By prioritizing the accuracy of ratings and ensuring the authenticity of consumer feedback, businesses can build trust and credibility, leading to enhanced consumer satisfaction and loyalty (Njoki Chege, 2021).

Factors that distinguish this study from other studies, this study specifically focuses on trustworthy recommendation systems and how consumers respond to the information received from these systems. The study aims to understand how consumers evaluate information sources and determine the reliability of trustworthy recommendation systems. IPT considers the emotional, cognitive, and behavioral experiences of individuals during the information processing process. This study examines consumers' experiences when using trustworthy recommendation systems and how these experiences influence their attitudes toward these systems.

These theoretical findings can contribute to the development of trustworthy recommendation systems and understanding the strategies designed to consumer trust in these systems. Additionally, they can provide important insights into how consumers can utilize trustworthy recommendation systems and how they can respond to the information provided by these systems.

5.3. Practical Implications

The findings of this study have practical implications for online players such as online marketplaces, retailers and businesses that utilize RSs. Firstly, retailers should focus on providing consumers with accurate ratings and reliable information about products. Maintaining transparency in rating systems and preventing fraudulent practices can contribute to consumer trust and satisfaction. Furthermore, encouraging genuine and informative consumer reviews can provide valuable insights to potential buyers and help them make informed decisions.

Additionally, for online players such as online marketplaces, retailers and businesses should invest in visual content strategies to engage consumers and improve the overall shopping experience. Encouraging consumers to share photos and videos of their purchased products, as well as incorporating visual media in product descriptions, can significantly impact consumer engagement and conversion rates. Leveraging user-generated visual content effectively can create a sense of authenticity and increase consumer confidence in product quality.

Furthermore, for online players such as online marketplaces, retailers and businesses should pay attention to the way products are recommended to consumers. Personalized recommendations based on consumer preferences, browsing history, and past purchases can enhance the relevance of product suggestions and increase the likelihood of conversion. By tailoring recommendations to individual needs and preferences, businesses can create a more personalized and satisfactory shopping experience.

5.4. Conclusion

This study utilized a DCE and Bayesian Design to analyze the attributes that consumers prioritize when making purchase decisions on online marketplaces. The results emphasize the significance of product ratings, comments with photos, the way products are recommended, and influencer comments in shaping online shoppers' choices.

Understanding the preferences of online shoppers provides important insights for businesses utilizing RSs and seeking to optimize their online platforms. By prioritizing accurate ratings, encouraging visual content, personalizing recommendations, and leveraging influencer partnerships, businesses can enhance consumer engagement, satisfaction, and ultimately drive conversion rates.

5.5. Limitations and future research

Even though this study provides insightful information, it is vital to recognize its limits. First off, the study was conducted just in Türkiye, which could limit how broadly the results can be applied. To gain a deeper knowledge of online shoppers' preferences in various circumstances, future research should attempt to duplicate the study in various locations.

Future research should also explore the dynamics of online shopping preferences across different demographic groups, including age, gender, and socioeconomic backgrounds. Understanding how these factors influence consumers' priorities and decision-making processes can provide further insights for businesses to tailor their strategies accordingly.

Moreover, comparing the results of this study with those from other regions and cultures would help in obtaining a more holistic view of online shoppers' preferences and behaviors. By considering the cultural and contextual variations, businesses can develop more targeted and effective approaches to cater to the needs and expectations of diverse consumer segments.

Additionally, the absence of the "rating of retailers" attribute in the study can be considered as a limitation. This means that there is no data available regarding the evaluation or rating of retailers. Rating of retailers is a criterion where consumers or consumer groups assess or rate retailers. This attribute is an important factor used to evaluate performance or reputation in the retail industry.

The absence of the rating of retailers in the study can lead to certain limitations. Like, Rating of retailers is a valuable source to understand consumer preferences. Without this information, the study may have a limited or incomplete understanding of consumer preferences. Competition in the retail sector is closely linked to consumer satisfaction and retailer performance. Rating of retailers can be a criterion used to compare the performance of competing retailers. Without this information, the study may be lacking in competitive analysis. Rating of retailers is often based on consumer feedback and reflects the consumer experience. This attribute can enhance the generalizability of the study's findings. The absence of the rating of retailers can make it challenging to evaluate and interpret the results from a consumer perspective.

Future studies can incorporate an evaluation system where consumers or consumer groups assess retailers based on various criteria such as consumer service, product quality, pricing, and overall satisfaction. This can be done through surveys, online platforms, or other data collection methods to collect and analyze consumer ratings.

Furthermore, collaborating with retail industry partners or associations can provide access to existing rating systems or databases that contain retailer evaluations. These partnerships can enhance the scope of the study.

REFERENCES

Adomavicius, G. and Tuzhilin, A. (2005). *Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions.* IEEE transactions on knowledge and data engineering, Vol. 17 (6), pp. 734-749.

Ahmadian, M., Ahmadi, M. and Ahmadian, S. (2022). *A reliable deep representation learning to improve trust-aware recommendation systems.* Expert Systems with Applications, Vol. 197, pp. 2-19.

Ahmadian, S., Ahmadian, M. and Jalili, M. (2022). *A deep learning based trust-and tag-aware recommender system.* Neurocomputing, Vol. 488, pp. 557-571.

Ahmadian, S., Joorabloo, N., Jalili, M., Meghdadi, M., Afsharchi, M. and Ren, Y. (2018, August). *A temporal clustering approach for social recommender systems.* In 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 1139-1144. IEEE.

Almana, A. M. and Mirza, A. A. (2013). *The impact of electronic word of mouth on consumers' purchasing decisions.* International Journal of Computer Applications, Vol. 82 (9), pp. 23-31.

Alaimo, C. and Kallinikos, J. (2021). *Managing by data: Algorithmic categories and organizing.* Organization Studies, Vol. 42 (9), pp. 1385-1407.

Alamdari, P. M., Navimipour, N. J., Hosseinzadeh, M., Safaei, A. A. and Darwesh, A. (2020). *A systematic study on the recommender systems in the E-commerce.* Ieee Access, Vol. 8, pp. 115694-115716.

Alwan, M. and Alshurideh, M. (2022). *The effect of digital marketing on purchase intention: Moderating effect of brand equity.* International Journal of Data and Network Science, Vol. 6 (3), pp. 837-848.

Anderson, E. W., Fornell, C. and Lehmann, D. R. (1994). *Customer satisfaction, market share, and profitability: Findings from Sweden.* Journal of marketing, Vol. 58 (3), pp. 53-66.

Andjelkovic, I., Parra, D. and O'Donovan, J. (2019). *Moodplay: interactive music recommendation based on artists' mood similarity.* International Journal of Human-Computer Studies, Vol. 121, pp. 142-159.

Atkinson, R. C. and Shiffrin, R. M. (1968). *Human memory: A proposed system and its control processes.* In Psychology of learning and motivation, Vol. 2, pp. 89-195.

Academic press.

Balabanis, G. and Diamantopoulos, A. (2016). *Consumer xenocentrism as determinant of foreign product preference: A system justification perspective.* Journal of International Marketing, Vol. 24(3), pp. 58-77.

Barber, S., Bekker, H., Marti, J., Pavitt, S., Khambay, B. and Meads, D. (2019). *Development of a discrete-choice experiment (DCE) to elicit adolescent and parent preferences for hypodontia treatment.* The Patient-Patient-Centered Outcomes Research, Vol. 12, pp. 137-148.

Barkan, O. and Koenigstein, N. (2016, September). *Item2vec: neural item embedding for collaborative filtering.* In 2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP), pp. 1-6. IEEE.

Batmaz, Z., Yurekli, A., Bilge, A. and Kaleli, C. (2019). *A review on deep learning for recommender systems: challenges and remedies.* Artificial Intelligence Review, Vol. 52, pp. 1-37.

Baum, D. and Spann, M. (2014). *The interplay between online consumer reviews and recommender systems: An experimental analysis.* International journal of electronic commerce, Vol. 19 (1), pp. 129-162.

Beel, J., Gipp, B., Langer, S. and Breitinger, C. (2016). *Paper recommender systems: a literature survey.* International Journal on Digital Libraries, Vol. 17, pp. 305-338.

Bell, R. M. and Koren, Y. (2007). Lessons from the Netflix prize challenge. Acm Sigkdd Explorations Newsletter, Vol. 9 (2), pp. 75-79.

Ben-Akiva, M., McFadden, D. and Train, K. (2019). *Foundations of stated preference elicitation: Consumer behavior and choice-based conjoint analysis.* Foundations and Trends® in Econometrics, Vol. 10 (1-2), pp. 1-144.

Berry, S. M., Carlin, B. P., Lee, J. J. and Muller, P. (2010). *Bayesian adaptive methods for clinical trials.* 1st edition. City: Florida. CRC press.

Betancourt, Y. and Ilarri, S. (2020). *Use of Text Mining Techniques for Recommender Systems.* In ICEIS, Vol. 1, pp. 780-787.

Bhardwaj, P. (2019). *Types of sampling in research.* Journal of the Practice of Cardiovascular Sciences, Vol. 5 (3), pp. 157.

Bhattacharya, T., Jaiswal, A. and Nagpal, V. (2016, September). *Web usage mining and text mining in the environment of web personalization for ontology development of recommender systems.* In 2016 5th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), pp. 78-85.

IEEE.

Bobadilla, J., Ortega, F., Hernando, A. and Gutiérrez, A. (2013). *Recommender systems survey*. Knowledge-based systems, Vol. 46, pp. 109-132.

Bock, D. E., Wolter, J. S. and Ferrell, O. C. (2020). *Artificial intelligence: disrupting what we know about services.* Journal of Services Marketing, Vol. 34 (3), pp. 317-334.

Boz, Z., Korhonen, V. and Koelsch Sand, C. (2020). *Consumer considerations for the implementation of sustainable packaging:* A review. Sustainability, Vol. 12, No. 6.

Breese, J. S., Heckerman, D. and Kadie, C. (2013). *Empirical analysis of predictive algorithms for collaborative filtering.*

Bridges, J. F., Hauber, A. B., Marshall, D., Lloyd, A., Prosser, L. A., Regier, D. A., ... and Mauskopf, J. (2011). *Conjoint analysis applications in health—a checklist: a report of the ISPOR Good Research Practices for Conjoint Analysis Task Force.* Value in health, Vol. 14 (4), pp. 403-413.

Brown, D. and Fiorella, S. (2013). *Influence marketing: How to create, manage, and measure brand influencers in social media marketing*. 1st edition. City: Indiana. Que Publishing.

Brusilovsky, P. and Millán, E. (2007). *User models for adaptive hypermedia and adaptive educational systems.* In The adaptive web: methods and strategies of web personalization, pp. 3-53. Berlin, Heidelberg: Springer Berlin Heidelberg.

Busetto, L., Wick, W. and Gumbinger, C. (2020). *How to use and assess qualitative research methods.* Neurological Research and practice, Vol. 2, pp. 1-10.

Casaló, L. V., Flavián, C. and Ibáñez-Sánchez, S. (2020). *Influencers on Instagram: Antecedents and consequences of opinion leadership.* Journal of business research, Vol. 117, pp. 510-519.

Castelluccio, M. (2006). *The music genome project.* Strategic Finance, pp. 57-59.

Cervone, D. and Pervin, L. A. (2022). *Personality: Theory and research.* 15th edition. City: New Jersey. John Wiley & Sons.

Chandramouli, B., Levandoski, J. J., Eldawy, A. and Mokbel, M. F. (2011, June). *Streamrec: a real-time recommender system.* In Proceedings of the 2011 ACM SIGMOD International Conference on Management of data, pp. 1243-1246.

Charu, C. A. (2016). *Recommender systems: The textbook*. 1st edition. City: New York. Springer.

Chatterjee, P. and Hoffman, D. L. (2018). *The impact of photos on trust and satisfaction in Airbnb.* Journal of Travel Research.

Chen, C. H., Nguyen, B., Klaus, P. P. and Wu, M. S. (2015). *Exploring electronic word-of-mouth (eWOM) in the consumer purchase decision-making process: the case of online holidays–evidence from United Kingdom (UK) consumers.* Journal of Travel & Tourism Marketing, Vol. 32 (8), pp. 953-970.

Chen, C., Meng, X., Xu, Z. and Lukasiewicz, T. (2017). *Location-aware personalized news recommendation with deep semantic analysis.* IEEE Access, Vol. 5, pp. 1624-1638.

Chen, Y. (2011, October). *Interface and interaction design for group and social recommender systems.* In Proceedings of the fifth ACM conference on Recommender systems, pp. 363-366.

Chen, Y. Y., Huang, C. L. and Hsieh, Y. C. (2020). *Exploring the influence of social media influencers on online purchase intention: The perception of social commerce experience.* Journal of Retailing and Consumer Services, Vol. 53, No. 101771.

Chen, Y., Fay, S. and Wang, Q. (2011). *The role of marketing in social media: How online consumer reviews evolve.* Journal of interactive marketing, Vol. 25 (2), pp. 85-94.

Chen, Z. S., Jang, J. S. R. and Lee, C. H. (2011). *A kernel framework for content-based artist recommendation system in music.* IEEE Transactions on Multimedia, Vol. 13 (6), pp. 1371-1380.

Cheung, C. M., Lee, M. K. and Rabjohn, N. (2008). *The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities.* Internet research, Vol. 18 (3), pp. 229-247.

Chevalier, J. A. and Mayzlin, D. (2006). *The effect of word of mouth on sales: Online book reviews.* Journal of marketing research, Vol. 43 (3), pp. 345-354.

Lim, X. J., Radzol, A. M., Cheah, J. and Wong, M. W. (2017). *The impact of social media influencers on purchase intention and the mediation effect of customer attitude.* Asian journal of business research, Vol. 7 (2), pp. 19-36.

Cintia Ganesha Putri, D., Leu, J. S. and Seda, P. (2020). *Design of an unsupervised machine learning-based movie recommender system.* Symmetry, Vol. 12 (2), pp. 185.

Creswell, J. W. and Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches.* 3rd edition. City: California. Sage publications.

Creswell, J. W. and Poth, C. N. (2016). *Qualitative inquiry and research design: Choosing among five approaches.* 4th edition. City: California. Sage publications.

Cui, L. Z., Guo, F. L., and Liang, Y. J. (2018, October). *Research overview of* *educational recommender systems.* In Proceedings of the 2nd International Conference on Computer Science and Application Engineering, pp. 1-7.

Dai, Y. N., Viken, G., Joo, E. and Bente, G. (2018). *Risk assessment in e-commerce: How sellers' photos, reputation scores, and the stake of a transaction influence buyers' purchase behavior and information processing.* Computers in Human Behavior, Vol. 84, pp. 342-351.

Da'u, A., Salim, N., Rabiu, I. and Osman, A. (2020). *Weighted aspect-based opinion mining using deep learning for recommender system.* Expert Systems with Applications, Vol. 140 (112871).

de Bekker-Grob, E. W., Ryan, M. and Gerard, K. (2012). *Discrete choice experiments in health economics: a review of the literature.* Health economics, Vol. 21 (2), pp. 145-172.

De Medio, C., Limongelli, C., Sciarrone, F. and Temperini, M. (2020). *MoodleREC: A recommendation system for creating courses using the moodle e-learning platform.* Computers in Human Behavior, Vol. 104 (106168).

De Veirman, M., Cauberghe, V. and Hudders, L. (2017). *Marketing through Instagram influencers: the impact of number of followers and product divergence on brand attitude.* International journal of advertising, Vol. 36 (5), pp. 798-828.

DeJonckheere, M. and Vaughn, L. M. (2019). *Semistructured interviewing in primary care research: a balance of relationship and rigour.* Family medicine and community health, Vol. 7 (2).

Dellarocas, C. (2003). *The digitization of word of mouth: Promise and challenges of online feedback mechanisms.* Management science, Vol. 49 (10) pp. 1407-1424.

Desai, D. (2019). *An empirical study of website personalization effect on users intention to revisit E-commerce website through cognitive and hedonic experience.* In Data Management, Analytics and Innovation: Proceedings of ICDMAI 2018, Vol. 2, pp. 3-19. Springer Singapore.

Deshpande, M. and Karypis, G. (2004). *Item-based top-n recommendation algorithms.* ACM Transactions on Information Systems (TOIS), Vol. 22 (1), pp. 143-177.

DeVellis, R. F. (2017). *An overview of item response theory. Scale development: theory and applications.* 4th edition. City: California. Sage publications. pp. 213-24.

Dhar, S. and Varshney, U. (2011). *Challenges and business models for mobile location-based services and advertising.* Communications of the ACM, Vol. 54 (5), pp. 121-128.

Diao, Q., Qiu, M., Wu, C. Y., Smola, A. J., Jiang, J. and Wang, C. (2014, August). *Jointly modeling aspects, ratings and sentiments for movie recommendation (JMARS).* In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 193-202.

Din, A. U., Han, H., Ariza-Montes, A., Vega-Muñoz, A., Raposo, A. and Mohapatra, S. (2022). *The impact of COVID-19 on the food supply chain and the role of e-commerce for food purchasing.* Sustainability, Vol. 14 (5), pp. 3074.

Duan, Y., Edwards, J. S. and Dwivedi, Y. K. (2019). *Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda.* International journal of information management, Vol. 48, pp. 63-71.

Duffett, R. G. (2015). *Facebook advertising's influence on intention-to-purchase and purchase amongst Millennials.* Internet research, Vol. 25 (4), pp. 498-526.

Ekstrand, M. D., Riedl, J. T. and Konstan, J. A. (2011). *Collaborative filtering recommender systems.* Foundations and Trends® in Human–Computer Interaction, Vol. 4 (2), pp. 81-173.

Feng, C., Khan, M., Rahman, A. U. and Ahmad, A. (2020). *News recommendation systems-accomplishments, challenges & future directions.* IEEE Access, Vol. 8, pp. 16702-16725.

Feng, Y., Chen, H. and Kong, Q. (2021). *An expert with whom I can identify: The role of narratives in influencer marketing.* International Journal of Advertising, Vol. 40 (7), pp. 972-993.

Filieri, R. and McLeay, F. (2014). *E-WOM and accommodation: An analysis of the factors that influence travelers' adoption of information from online reviews.* Journal of travel research, Vol. 53 (1), pp. 44-57.

Fleming, J. (2018). *Recognizing and resolving the challenges of being an insider researcher in work-integrated learning.* International Journal of Work-Integrated Learning, Vol. 19 (3), pp. 311-320.

Forman, C. and Ghose, A. (2008). *Predicting the value of consumer reviews: A sentiment analysis approach.* Proceedings of the International Conference on Information Systems.

Fraenkel, J., Wallen, N. and Hyun, H. (2018). *How to design and evaluate research in education.* 10th edition. City: San Francisco. McGraw-Hill.

Frias-Martinez, E., Chen, S. Y. and Liu, X. (2009). *Evaluation of a personalized digital* *library based on cognitive styles: Adaptivity vs. adaptability*. International Journal of Information Management, Vol. 29 (1), pp. 48-56.

Gao, J., Zhang, C., Wang, K. and Ba, S. (2012). *Understanding online purchase decision making: The effects of unconscious thought, information quality, and information quantity*. Decision Support Systems, Vol. 53 (4), pp. 772-781.

García-Pedrajas, N., Herrera, F., Fyfe, C., Sánchez, J. M. B. and Ali, M. (Eds.). (2011). *Trends in Applied Intelligent Systems: 23rd International Conference on Industrial Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE 2010, Cordoba, Spain, June 1-4, 2010, Proceedings, Part II*, Vol. 6097. Springer.

Gavilan, D., Avello, M. and Martinez-Navarro, G. (2018). *The influence of online ratings and reviews on hotel booking consideration*. Tourism Management, Vol. 66, pp. 53-61.

Gedikli, F., Jannach, D. and Ge, M. (2014). How should I explain? A comparison of different explanation types for recommender systems. International Journal of Human-Computer Studies, Vol. 72 (4), pp. 367-382.

Geetha, G., Safa, M., Fancy, C. and Saranya, D. (2018, April). *A hybrid approach using collaborative filtering and content based filtering for recommender system*. In Journal of Physics: Conference Series, Vol. 1000, pp. 012101. IOP Publishing.

Gelman, A., Carlin, J. B., Stern, H. S. and Rubin, D. B. (1995). *Bayesian data analysis.* 1st edition. City: New York. Chapman and Hall/CRC.

Ghose, A. and Ipeirotis, P. G. (2010). *Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics.* IEEE transactions on knowledge and data engineering, Vol. 23 (10), pp. 1498-1512.

Giubilini, A. and Minerva, F. (2019, May). *Enhancing equality.* In The Journal of Medicine and Philosophy: A Forum for Bioethics and Philosophy of Medicine, Vol. 44 (3), pp. 335-354. US: Oxford University Press.

Godes, D. and Mayzlin, D. (2004). *Using online conversations to study word-of-mouth communication.* Marketing science, Vol. 23 (4), pp. 545-560.

Goldberg, D., Nichols, D., Oki, B. M. and Terry, D. (1992). *Using collaborative filtering to weave an information tapestry.* Communications of the ACM, Vol. 35 (12), pp. 61-70.

Goranitis, I., Best, S., Stark, Z., Boughtwood, T. and Christodoulou, J. (2021). *The value of genomic sequencing in complex pediatric neurological disorders: a discrete* *choice experiment.* Genetics in Medicine, Vol. 23 (1), pp. 155-162.

Grafström, J., Jakobsson, L. and Wiede, P. (2018). *The impact of influencer marketing on consumers' attitudes.*

Greengard, S. (2021). *The internet of things.* Revised and Updated Edition. City: Cambridge. MIT press.

Guo, Q., Zhuang, F., Qin, C., Zhu, H., Xie, X., Xiong, H. and He, Q. (2020). *A survey on knowledge graph-based recommender systems.* IEEE Transactions on Knowledge and Data Engineering, Vol. 34 (8), pp. 3549-3568.

Hardesty, L. (2019). *The history of Amazon's recommendation algorithm.* Amazon Science, Vol. 22.

Hayashi, Y., Orita, R. and Kajiwara, S. (2017, February). *Negative electronic word-of-mouth can support product recommendation: experimental investigation.* In Companion of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, pp. 191-194.

Helter, T. M. and Boehler, C. E. H. (2016). *Developing attributes for discrete choice experiments in health: a systematic literature review and case study of alcohol misuse interventions.* Journal of substance use, Vol. 21 (6), pp. 662-668.

Hennig-Thurau, T., Walsh, G. and Walsh, G. (2003). *Electronic word-of-mouth: Motives for and consequences of reading customer articulations on the Internet.* International journal of electronic commerce, Vol. 8 (2), pp. 51-74.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G. and Gremler, D. D. (2004). *Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet?.* Journal of interactive marketing, Vol. 18 (1), pp. 38-52.

Hensher, D. A., Rose, J. M. and Greene, W. H. (2005). *Applied choice analysis: a primer.* 1st edition. City: Cambridge. Cambridge university press.

Herlocker, J. L., Konstan, J. A. and Riedl, J. (2000, December). *Explaining collaborative filtering recommendations.* In Proceedings of the 2000 ACM conference on Computer supported cooperative work, pp. 241-250.

Hosseini, M., Rahimi-Kian, A., and Moeini-Jazani, M. (2020). *Social media influencers' effects on consumers' purchasing intention.* Journal of Retailing and Consumer Services, Vol. 53 (101771).

Hu, N., Liu, L. and Zhang, J. J. (2008). *Do online reviews affect product sales? The role of reviewer characteristics and temporal effects.* Information Technology and management, Vol. 9, pp. 201-214.

Sun, Z. (2021). *Reducing the Gulfs in Human-Computer Communication: Exploring the Effects of Non-verbal Metaphors.* Hong Kong University of Science and Technology (Hong Kong).

Huang, L., and Chen, Y. (2017). *How does the sparsity of online product reviews affect consumer purchase behavior?* Journal of Interactive Marketing, Vol. 39, pp. 70-84.

Huang, Y. H., and Hsieh, Y. J. (2016). *Information processing, website design, and consumer decisions: An investigation of the information processing theory in online shopping.* Electronic Commerce Research and Applications, Vol. 16, pp. 22-37.

Hwangbo, H., Kim, Y. S., and Cha, K. J. (2018). *Recommendation system development for fashion retail e-commerce.* Electronic Commerce Research and Applications, Vol. 28, pp. 94-101.

İAB Türkiye. (2022). *Medya Yatırımları Tahmini 2022 H1.* [Online] Available at: https://iabtr.org/UploadFiles/PageFiles/MedyaYat%C4%B1r%C4%B1mlar%C4%B1Tahmini_2022H111102022114624.pdf (Accessed: 1 October 2022).

Iwanaga, J., Nishimura, N., Sukegawa, N. and Takano, Y. (2019). *Improving collaborative filtering recommendations by estimating user preferences from clickstream data.* Electronic Commerce Research and Applications, Vol. 37 (100877).

Jannach, D., Zanker, M., Felfernig, A. and Friedrich, G. (2011). *An introduction to recommender systems.* 1st edition. City: New York. Cambridge, Vol. 10 (1941904).

Janssen, E. M., Marshall, D. A., Hauber, A. B. and Bridges, J. F. (2017). *Improving the quality of discrete-choice experiments in health: how can we assess validity and reliability?.* Expert review of pharmacoeconomics & outcomes research, Vol. 17 (6), pp. 531-542).

Janssen, E. M., Segal, J. B. and Bridges, J. F. (2016). *A framework for instrument development of a choice experiment: an application to type 2 diabetes.* The Patient-Patient-Centered Outcomes Research, Vol. 9 (5), pp. 465-479.

Javed, U. vd. (2021). *A review of content-based and context-based recommendation systems.* International Journal of Emerging Technologies in Learning (iJET), Vol. 16 (3), pp. 274-306.

Jazi, S. Y., Kaedi, M. and Fatemi, A. (2021). *An emotion-aware music recommender system: bridging the user's interaction and music recommendation.* Multimedia Tools and Applications, Vol. 80 (9), pp. 13559-13574.

Jiang, L., Cheng, Y., Yang, L., Li, J., Yan, H. and Wang, X. (2019). *A trust-based* *collaborative filtering algorithm for E-commerce recommendation system.* Journal of ambient intelligence and humanized computing, Vol. 10, pp. 3023-3034.

Johnson, R. B. and Christensen, L. B. (2019). *Educational Research: Quantitative, Qualitative, and Mixed Approaches.* 6th edition. City: California. SAGE Publications.

Jones, G. J. (2005, April). *Challenges and opportunities of context-aware information access.* In International Workshop on Ubiquitous Data Management, pp. 53-60. IEEE.

Jonker, M. F., Donkers, B., de Bekker-Grob, E. W. and Stolk, E. A. (2018). *Effect of level overlap and color coding on attribute non-attendance in discrete choice experiments.* Value in Health, Vol. 21 (7), pp. 767-771.

Joyce, J. (2006). *Pandora and the Music Genome Project, song structure analysis tools facilitate new music discovery.* Scientific Computing, Vol. 23 (14), pp. 40-41.

Jugovac, M. and Jannach, D. (2017). In*teracting with recommenders—overview and research directions.* ACM Transactions on Interactive Intelligent Systems (TiiS), Vol. 7 (3), pp. 1-46.

Kafkas, K., Perdahçı, Z. N. and Aydın, M. N. (2021). *Discovering consumer purchase patterns in product communities: an empirical study on co-purchase behavior in an online marketplace.* Journal of Theoretical and Applied Electronic Commerce Research, Vol. 16 (7), pp. 2965-2980.

Karakaya, F. and Aydın, S. (2019). *The effect of consumer reviews and ratings on online product sales: A meta-analysis.* Journal of Business Research, Vol. 98, pp. 1-10.

Kaur, A., Goyal, R. and Aggarwal, P. (2017). *The influence of product ratings on purchase decisions: An empirical study.* Journal of Retailing and Consumer Services, Vol. 36, pp. 1-11.

Kermany, N. R. and Alizadeh, S. H. (2017). *A hybrid multi-criteria recommender system using ontology and neuro-fuzzy techniques.* Electronic Commerce Research and Applications, Vol. 21, pp. 50-64.

Kim, H. N., Ji, A. T., Ha, I. and Jo, G. S. (2010). *Collaborative filtering based on collaborative tagging for enhancing the quality of recommendation.* Electronic Commerce Research and Applications, Vol. 9 (1), pp. 73-83.

Kim, S. S., Lee, J. and Prideaux, B. (2014). *Effect of celebrity endorsement on tourists' perception of corporate image, corporate credibility and corporate loyalty.* International Journal of Hospitality Management, Vol. 37, pp. 131-145.

Knudsen, E. S., Lien, L. B., Timmermans, B., Belik, I. and Pandey, S. (2021). *Stability* *in turbulent times? The effect of digitalization on the sustainability of competitive advantage.* Journal of Business Research, Vol. 128, pp. 360-369.

Konstan, J. A., Riedl, J. and Herlocker, J. (2012). *Recommender systems: from algorithms to user experience.* User Modeling and User-Adapted Interaction, Vol. 22 (1-2), pp. 101-127.

Koren, Y. (2010). *Factor in the neighbors: Scalable and accurate collaborative filtering.* ACM Transactions on Knowledge Discovery from Data (TKDD), Vol. 4 (1), pp. 1-24.

Kripesh, A. S., Prabhu, H. M. and Sriram, K. V. (2020). *An empirical study on the effect of product information and perceived usefulness on purchase intention during online shopping in India.* International Journal of Business Innovation and Research, Vol. 21 (4), pp. 509-522.

Kruschke, J. (2014). *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan.*

Lai, C. C. and Tsai, C. F. (2018). *An application of discrete choice experiment for evaluating the effectiveness of personalized recommendations for online shopping.* International Journal of Information Management, Vol. 38 (3), pp. 496-506.

Lancsar, E. and Louviere, J. (2008). *Conducting discrete choice experiments to inform healthcare decision making: a user's guide.* Pharmacoeconomics, Vol. 26, pp. 661-677.

Lee, H. J. and Kim, Y. K. (2018). *Effects of reviews with photos on consumers' purchase intention in e-commerce contexts: The moderating role of product type.* Journal of Research in Interactive Marketing, Vol. 12 (3), pp. 262-280.

Lee, J., Park, D. H. and Han, I. (2008). *The effect of negative online consumer reviews on product attitude: An information processing view.* Electronic commerce research and applications, Vol. 7 (3), pp. 341-352.

Lee, S. K., Cho, Y. H. and Kim, S. H. (2010). *Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations.* Information Sciences, Vol. 180 (11), pp. 2142-2155.

Lee, S. and Lee, D. (2018). *A personalized channel recommendation and scheduling system considering both section video clips and full video clips.* Plos one, Vol. 13 (7).

Li, S. G., Zhang, Y. Q., Yu, Z. X. and Liu, F. (2021). *Economical user-generated content (UGC) marketing for online stores based on a fine-grained joint model of the consumer purchase decision process.* Electronic Commerce Research, Vol. 21, pp. 1083-1112.

Li, T., Jin, L., Wu, Z. and Chen, Y. (2019). *Combined recommendation algorithm based on improved similarity and forgetting curve.* Information, Vol. 10 (4), pp. 130.

Li, X., Wang, H. and Yan, X. (2015). *Accurate recommendation based on opinion mining. In Genetic and Evolutionary Computing: Proceeding of the Eighth International Conference on Genetic and Evolutionary Computing, October 18-20, 2014, Nanchang, China,* pp. 399-408. Springer International Publishing.

Liang, T. P., Ho, Y. T., Li, Y. W. and Turban, E. (2011). *What drives social commerce: The role of social support and relationship quality.* International journal of electronic commerce, Vol. 16 (2), pp. 69-90.

Libby, R. and Lewis, B. L. (1977). *Human information processing research in accounting: The state of the art.* Accounting, Organizations and Society, Vol. 2 (3), pp. 245-268.

Lifke, D. and Syroid, C. (2016). *Design of Experiments (DOE) Choice Design vs. Forced Ranking* (SAND2016-8005C). Sandia National Lab. (SNL-NM), Albuquerque, NM (United States).

Lim, J. and Ayyagari, R. (2018). *Investigating the determinants of telepresence in the e-commerce setting.* Computers in Human Behavior, Vol. 85, pp. 360-371.

Linden, G., Smith, B. and York, J. (2003). *Amazon.com recommendations: Item-to-item collaborative filtering.* IEEE Internet computing, Vol. 7 (1), pp. 76-80.

Liu, J., Dolan, P. and Pedersen, E. R. (2010, February). *Personalized news recommendation based on click behavior.* In Proceedings of the 15th international conference on Intelligent user interfaces, pp. 31-40.

Liu, R. S. and Yang, T. C. (2016, August). *Improving Recommendation Accuracy by Considering Electronic Word-of-Mouth and the Effects of Its Propagation Using Collective Matrix Factorization.* In 2016 IEEE 14th Intl Conf on Dependable, Autonomic and Secure Computing, 14th Intl Conf on Pervasive Intelligence and Computing, 2nd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech), pp. 696-703. IEEE.

Liu, T., Tsang, W., Huang, F., Lau, O. Y., Chen, Y., Sheng, J., ... and Ming, W. K. (2021). *Patients' preferences for artificial intelligence applications versus clinicians in disease diagnosis during the SARS-CoV-2 pandemic in China: Discrete choice experiment.* Journal of Medical Internet Research, Vol. 23 (2).

Liu, W., Müllner, M. and West, M. (2018). *Bayesian design of experiments.* Annual

Review of Statistics and Its Application, Vol. 5, pp. 115-140.
Liu, Y. (2006). *Word of mouth for movies: Its dynamics and impact on box office revenue.* Journal of marketing, Vol. 70 (3), pp. 74-89.
Lombardi, I. and Vernero, F. (2017). *What and who with: A social approach to double-sided recommender.* International Journal of Human-Computer Studies, Vol. 101, pp. 62-75.
Lu, J., Wu, D., Mao, M., Wang, W. and Zhang, G. (2015). *Recommender system application developments: a survey.* Decision support systems, Vol. 74, pp. 12-32.
Lu, X., He, S., Lian, S., Ba, S. and Wu, J. (2020). *Is user-generated content always helpful? The effects of online forum browsing on consumers' travel purchase decisions.* Decision Support Systems, Vol. 137 (113368).
Lune, H. and Berg, B. L. (2017). *Qualitative research methods for the social sciences.* 8th edition. City: Vivar. Pearson.
Lv, J. and Liu, X. (2022). *The Impact of Information Overload of E-Commerce Platform on Consumer Return Intention: Considering the Moderating Role of Perceived Environmental Effectiveness.* International Journal of Environmental Research and Public Health, Vol. 19 (13), pp. 8060.
Maier, E. and Wieringa, J. (2021). *Acquiring consumers through online marketplaces? The effect of marketplace sales on sales in a retailer's own channels.* International Journal of Research in Marketing, Vol. 38 (2), pp. 311-328.
Maity, A. R. I. J. I. T. (2014). *Impact of External Influencer Recommendation in Purchase Behavior Process of Selection of Cement for Construction.* International Journal of Business and Management Invention, Vol. 3 (8), pp. 01-11.
Majid, I. and Verma, S. (2021). *Web 2.0 technological tools in teaching and learning.* Majid, I. and Verma, S.(2018). Web, 2, pp. 55-60.
McAuley, J., Targett, C., Shi, Q. and Van Den Hengel, A. (2015, August). *Image-based recommendations on styles and substitutes.* In Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval, pp. 43-52.
Milano, S., Taddeo, M. and Floridi, L. (2020). *Recommender systems and their ethical challenges.* Ai and Society, Vol. 35, pp. 957-967.
Milano, S., Taddeo, M. and Floridi, L. (2021). *Ethical aspects of multi-stakeholder recommendation systems.* The information society, Vol. 37 (1), pp. 35-45.
Miller, G. A. (1956). *The magical number seven, plus or minus two: Some limits on*

our capacity for processing information. Psychological review, Vol. 63 (2), pp. 81.

Mir, A. A. and Hassan, S. (2018). *Exploring the role of Web 2.0 in Digital Entrepreneurship.* Business Review, Vol. 22 (1).

Moe, W. W. and Trusov, M. (2011). *The value of social dynamics in online product ratings forums.* Journal of Marketing Research, Vol. 48 (3), pp. 444-456.

Mohammadi, N. and Rasoolzadegan, A. (2022). *A two-stage location-sensitive and user preference-aware recommendation system.* Expert Systems with Applications, Vol. 191 (116188).

Moradi, P. and Ahmadian, S. (2015). *A reliability-based recommendation method to improve trust-aware recommender systems.* Expert Systems with Applications, Vol. 42 (21), pp. 7386-7398.

Moser, A. and Korstjens, I. (2018). *Series: Practical guidance to qualitative research. Part 3: Sampling, data collection and analysis.* European journal of general practice, Vol. 24 (1), pp. 9-18.

Moustaki, I. (2020). *Bayesian model selection in social research.* Sociological Methods and Research.

Najafabadi, M. K., Mahrin, M. N. R., Chuprat, S. and Sarkan, H. M. (2017). *Improving the accuracy of collaborative filtering recommenders using clustering and association rules mining on implicit data.* Computers in Human Behavior, Vol. 67, pp. 113-128.

Netflix. (2021). *How Netflix Recommendations Work.* [Online] Available at: https://help.netflix.com/en/node/100639 (Accessed: 1 January 2021).

Njoki Chege, C. (2021). *Examining the influence of service reliability on customer satisfaction in the insurance industry in Kenya.*

Okada, K., Tan, P. X. and Kamioka, E. (2021, July). *Five-Factor Musical Preference Prediction for Solving New User Cold-Start Problem in Content-Based Music Recommender System.* In 2021 12th International Conference on Information, Intelligence, Systems and Applications (IISA), pp. 1-7. IEEE.

Oramas, S., Ostuni, V. C., Noia, T. D., Serra, X. and Sciascio, E. D. (2016). *Sound and music recommendation with knowledge graphs.* ACM Transactions on Intelligent Systems and Technology (TIST), Vol. 8 (2), pp. 1-21.

Orsolini, L., Francesconi, G., Papanti, D., Giorgetti, A. and Schifano, F. (2015). *Profiling online recreational/prescription drugs' customers and overview of drug vending virtual marketplaces.* Human Psychopharmacology: Clinical and Experimental, Vol. 30 (4), pp. 302-318.

Padem, H., Göksu, A. and Konaklı, Z. (2012). *Araştırma yöntemleri.* Sarajevo: International Burch University Yayınları.

Pan, X., Hou, L. and Liu, K. (2022). *The effect of product distance on the eWOM in recommendation network.* Electronic Commerce Research, Vol. 22 (3), pp. 901-924.

Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N. and Chrissikopoulos, V. (2017). *Sense and sensibility in personalized e-commerce: How emotions rebalance the purchase intentions of persuaded customers.* Psychology & Marketing, Vol. 34 (10), pp. 972-986.

Parida, P. P., Gourisaria, M. K., Pandey, M. and Rautaray, S. S. (2021). *Collaborative-based movie recommender system—a proposed model.* In Smart Computing Techniques and Applications: Proceedings of the Fourth International Conference on Smart Computing and Informatics, Vol. 1, pp. 561-571. Springer Singapore.

Park, C. and Lee, T. M. (2009). *Information direction, website reputation and eWOM effect: A moderating role of product type.* Journal of Business research, Vol. 62 (1), pp. 61-67.

Park, D. H., Lee, J. and Han, I. (2007). *The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement.* International journal of electronic commerce, Vol. 11 (4), pp. 125-148.

Park, J., Park, J., Kim, M. and Oh, H. (2019). *Influencer Attribute Analysis based Recommendation System.* Journal of the Korea Institute of Information and Communication Engineering, Vol. 23 (11), pp. 1321-1329.

Park, Y. J. and Chang, K. N. (2009). *Individual and group behavior-based consumer profile model for personalized product recommender.* Expert Systems with Applications, Vol. 36 (2), pp. 1932-1939.

Pazzani, M. J. and Billsus, D. (2007). *Content-based recommendation systems.* In The adaptive web, pp. 325-341. Springer, Berlin, Heidelberg.

Poon, Y. L., Lim, C. Y., Yong, D. M. K., Hiribae, C. M. and Tan, A. Y. W. (2014). *eWoM Influence on Booking Intention: A study of hotels in KL* (Doctoral dissertation, UTAR).

Powney, J. and Watts, M. (2018). *Interviewing in educational research.* 1st edition. City: London. Routledge.

Priambodo, I. T., Sasmoko, S., Abdinagoro, S. B. and Bandur, A. (2021). *E-Commerce readiness of creative industry during the COVID-19 pandemic in Indonesia.* The Journal of Asian Finance, Economics and Business, Vol. 8 (3), pp. 865-873.

Punch, K. F. (2013). *Introduction to social research: Quantitative and qualitative approaches.* 3rd edition. City: London. sage.

Pyle, M. A., Smith, A. N. and Chevtchouk, Y. (2021). *In eWOM we trust: Using naïve theories to understand consumer trust in a complex eWOM marketspace.* Journal of Business Research, Vol. 122, pp. 145-158.

Qi, J., Zhang, Z., Jeon, S. and Zhou, Y. (2016). *Mining consumer requirements from online reviews: A product improvement perspective.* Information and Management, Vol. 53 (8), pp. 951-963.

Rafter, R. (2010). *Evaluation and conversation in collaborative filtering* (Doctoral dissertation, University College Dublin).

Rana, A. and Deeba, K. (2019, November). *Online book recommendation system using collaborative filtering (with Jaccard similarity).* In Journal of Physics: Conference Series, Vol. 1362 (1), pp. 012130. IOP Publishing.

Ranganathan, P. and Pramesh, C. S. (2017). *Bayesian methods in clinical research: a brief introduction.* Indian journal of orthopaedics, Vol. 51 (4), pp. 388-392.

Reinartz, W., Wiegand, N. and Imschloss, M. (2019). *The impact of digital transformation on the retailing value chain.* International Journal of Research in Marketing, Vol. 36 (3), pp. 350-366.

Resnick, P. and Varian, H. R. (1997). *Recommender systems.* Communications of the ACM, Vol. 40 (3), pp. 56-58.

Ricci, F., Rokach, L. and Shapira, B. (2015). *Recommender systems: introduction and challenges.* Recommender systems handbook, pp. 1-34.

Rivas, A., Chamoso, P., González-Briones, A., Casado-Vara, R. and Corchado, J. M. (2019). *Hybrid job offer recommender system in a social network.* Expert Systems, Vol. 36 (4).

Riyahi, M. and Sohrabi, M. K. (2020). *Providing effective recommenders in discussion groups using a new hybrid recommender system based on implicit ratings and semantic similarity.* Electronic Commerce Research and Applications, Vol. 40 (100938).

Roy, K., Zvonkovic, A., Goldberg, A., Sharp, E. and LaRossa, R. (2015). *Sampling richness and qualitative integrity: Challenges for research with families.* Journal of Marriage and Family, Vol. 77 (1), pp. 243-260.

Ryan, M., Kolstad, J. R., Rockers, P. C. and Dolea, C. (2012). *How to conduct a discrete choice experiment for health workforce recruitment and retention in remote* *and rural areas: a user guide with case studies* (74489), pp. 1-94. The World Bank.

Ryan, M., Gerard, K. and Amaya-Amaya, M. (Eds.). (2008). *Using discrete choice experiments to value health and health care,* Vol. 11. Springer Science and Business Media.

Salvador, J. T. (2016). *Revisiting the philosophical underpinnings of qualitative research.* International Education and Research Journal, Vol. 2 (6), pp. 4-6.

Sánchez-Moreno, D., Pérez-Marcos, J., Gil González, A. B., Batista, V. L. and Moreno-García, M. N. (2019). *Social influence-based similarity measures for user-user collaborative filtering applied to music recommendation.* In Distributed Computing and Artificial Intelligence, Special Sessions, 15th International Conference 15, pp. 267-274. Springer International Publishing.

Saranya, K. G. and Sadhasivam, G. S. (2012). *A personalized online news recommendation system.* International Journal of Computer Applications, Vol. 57 (18).

Sarwar, B. M., Konstan, J. A. and Riedl, J. (2001). *Item-based collaborative filtering recommendation algorithms.* In Proceedings of the 10th international conference on World Wide Web, pp. 285-295. ACM.

Schafer, J. B., Frankowski, D., Herlocker, J. and Sen, S. (2007). *Collaborative filtering recommender systems.* In The adaptive web: methods and strategies of web personalization, pp. 291-324. Berlin, Heidelberg: Springer Berlin Heidelberg.

Schmalz, M., Carter, M. and Lee, J. H. (2018). *It's Not You, It's Me: Identity, Self-Verification, and Amazon Reviews.* ACM SIGMIS Database: the DATABASE for Advances in Information Systems, Vol. 49 (2), pp. 79-92.

Schultz, D. and Schultz, S. (2007). *A history of modern psychology.* 10th edition. City: Boston. Cengage Learning.

Schunk, D. H. (2012). *Learning theories an educational perspective.* 6th edition. City: Boston. Pearson.

Seitz, V. and Kim, D. J. (2021). *Information processing in online retailing: A review and future research directions.* Journal of Business Research, Vol. 129, pp. 312-327.

Sekaran, U. and Bougie, R. (2016). *Research methods for business: A skill building approach.* 7th edition. City: Trento. john wiley and sons.

Sen, S. and Lerman, D. (2007). *Why are you telling me this? An examination into negative consumer reviews on the web.* Journal of interactive marketing, Vol. 21 (4), pp. 76-94.

Sever, I., Verbič, M. and Sever, E. K. (2019). *Estimating willingness-to-pay for health care: a discrete choice experiment accounting for non-attendance to the cost attribute.* Journal of Evaluation in Clinical Practice, Vol. 25 (5), pp. 843-849.

Shah, K., Salunke, A., Dongare, S. and Antala, K. (2017, March). R*ecommender systems: An overview of different approaches to recommendations.* In 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), pp. 1-4. IEEE.

Sheikh, Z., Yezheng, L., Islam, T., Hameed, Z. and Khan, I. U. (2019). *Impact of social commerce constructs and social support on social commerce intentions.* Information Technology & People, Vol. 32 (1), pp. 68-93.

Shin, D. (2020). *How do users interact with algorithm recommender systems? The interaction of users, algorithms, and performance.* Computers in Human Behavior, Vol. 109 (106344).

Shu, J., Shen, X., Liu, H., Yi, B. and Zhang, Z. (2018). *A content-based recommendation algorithm for learning resources.* Multimedia Systems, Vol. 24 (2), pp. 163-173.

Smith, B. and Linden, G. (2017). *Two decades of recommender systems at Amazon.com.* Ieee internet computing, Vol. 21 (3), pp. 12-18.

Solso, R., Maclin, O. H. and Kimberly, M. (2007). *Cognitive Psychology: International Editon.* 8th edition. City: Harlow. Pearson.

Sousa, R. D., Cristian, L., Feitosa, L., Choi, E., Nguyen, T. A., Min, D. and Silva, F. A. (2023). *Performability Evaluation and Sensitivity Analysis of a Video Streaming on Demand Architecture.* Applied Sciences, Vol. 13 (2), pp. 998.

Sparks, B. A. and Browning, V. (2011). *The impact of online reviews on hotel booking intentions and perception of trust.* Tourism management, Vol. 32 (6), pp. 1310-1323.

Suchal, J. and Návrat, P. (2010, September). *Full text search engine as scalable k-nearest neighbor recommendation system.* In IFIP International Conference on Artificial Intelligence in Theory and Practice, pp. 165-173. Springer, Berlin, Heidelberg.

Sumpton, D., Kelly, A., Craig, J. C., Hassett, G., Kane, B., Oliffe, M., ... and Howell, M. (2022). *Preferences for biologic treatment in patients with psoriatic arthritis: a discrete choice experiment.* Arthritis Care & Research, Vol. 74 (8), pp. 1234-1243.

Sun, Z., Guo, Q., Yang, J., Fang, H., Guo, G., Zhang, J. and Burke, R. (2019). *Research commentary on recommendations with side information: A survey and research* *directions.* Electronic Commerce Research and Applications, Vol. 37 (100879).

Sundaram, D. S., Mitra, K. and Webster, C. (1998). *Word-of-mouth communications: A motivational analysis.* Advances in consumer research, Vol. 25 (1), pp. 527-531.

T.C. Ticaret Bakanlığı. (2021). *E-Ticaret Bülteni 2021 İlk 6 Ay.* [Online] Available at: https://www.eticaret.gov.tr/dnnqthgzvawtdxraybsaacxtymawm/content/FileManager/Dosyalar/E-TI%CC%87CARET%20B%C3%9CLTEN%C4%B0%202021%20%C4%B0lk%206%20ay.pdf (Accessed: 1 July 2021).

Taghavi, M., Bentahar, J., Bakhtiyari, K. and Hanachi, C. (2018). *New insights towards developing recommender systems.* The computer journal, Vol. 61 (3), pp. 319-348.

Tarus, J. K., Niu, Z. and Mustafa, G. (2018). *Knowledge-based recommendation: a review of ontology-based recommender systems for e-learning.* Artificial intelligence review, Vol. 50, pp. 21-48.

Tavakol, M. and Dennick, R. (2011). *Making sense of Cronbach's alpha.* International journal of medical education, Vol. 2, No. 53.

Tewari, A. S., Kumar, A. and Barman, A. G. (2014, February). *Book recommender system based on combine features of content based filtering, collaborative filtering and association rule mining.* In 2014 IEEE International Advance Computing Conference (IACC), pp. 500-503. IEEE.

Tian, Y., Zheng, B., Wang, Y., Zhang, Y. and Wu, Q. (2019). *College library personalized recommendation system based on hybrid recommendation algorithm.* Procedia CIRP, Vol. 83, pp. 490-494.

Tintarev, N. and Masthoff, J. (2010). *Designing and evaluating explanations for recommender systems.* In Recommender systems handbook, pp. 479-510. Boston, MA: Springer US.

TripAdvisor. (2021). *About TripAdvisor.* [Online] Available at: https://www.tripadvisor.com/TripAdvisorInsights/n2666/about-tripadvisor (Accessed: 1 January 2021).

Trochim, W. M. K. and Donnelly, J. P. (2008). *The research methods knowledge base.* Cengage Learning.

Trzebiński, W. and Marciniak, B. (2022). *Meaning or importance? E-commerce consumers interest in product features presented in online offerings: The role of self-relevance and information processing.* Journal of Internet Commerce, pp. 1-20.

US Food and Drug Administration. (2016). *Patient preference information—voluntary submission, review in premarket approval applications, humanitarian device exemption applications, and de novo requests, and inclusion in decision summaries and device labeling.* Food and Drug Administration staff, and other stakeholders, 2017.

Ventre, I. and Kolbe, D. (2020). *The impact of perceived usefulness of online reviews, trust and perceived risk on online purchase intention in emerging markets: A Mexican perspective.* Journal of International Consumer Marketing, Vol. 32 (4), pp. 287-299.

Verma, S. and Yadav, N. (2021). *Past, present, and future of electronic word of mouth (EWOM).* Journal of Interactive Marketing, Vol. 53 (1), pp. 111-128.

Viglia, G., Minazzi, R. and Buhalis, D. (2016). *The influence of e-word-of-mouth on hotel occupancy rate.* International Journal of Contemporary Hospitality Management.

Virdi, P., Kalro, A. D. and Sharma, D. (2020). *Consumer acceptance of social recommender systems in India.* Online Information Review, Vol, 44(3), pp. 723-744.

Wang, H., Wang, N. and Yeung, D. Y. (2015, August). *Collaborative deep learning for recommender systems.* In Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining, pp. 1235-1244.

Wang, H., Wang, Z. and Zhang, W. (2018, April). *Quantitative analysis of Matthew effect and sparsity problem of recommender systems.* In 2018 IEEE 3rd International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), pp. 78-82. IEEE.

Wang, J., Molina, M. D. and Sundar, S. S. (2020). *When expert recommender contradicts peer opinion: Relative social influence of valence, group identity and artificial intelligence.* Computers in Human Behavior, Vol. 107 (106278).

Wang, X. and Emurian, H. H. (2005). *An overview of online trust: Concepts, elements, and implications.* Computers in Human Behavior, Vol. 21 (1), pp. 105-125.

Woolfolk, A. (2016). *Educational psychology: Active learning edition.* 13^{th} edition. City: Boston. Pearson.

Xie, K. L., So, K. K. F. and Wang, W. (2017). *Joint effects of management responses and online reviews on hotel financial performance: A data-analytics approach.* International Journal of Hospitality Management, Vol. 62, pp. 101-110.

Xu, X., Dutta, K. and Ge, C. (2018). *Do adjective features from user reviews address sparsity and transparency in recommender systems?.* Electronic Commerce Research and Applications, Vol. 29, pp. 113-123.

Yang, X., Guo, Y., Liu, Y. and Steck, H. (2014). *A survey of collaborative filtering based social recommender systems.* Computer communications, Vol. 41, pp. 1-10.

Yang, Z., Xia, D., Liu, J., Zheng, C., Qu, Y., Chen, Y. and Zhang, C. (2021). *Fusion of internal similarity to improve the accuracy of recommendation algorithm.* Journal on Internet of Things, Vol. 2 (65).

Yang, Z. and Mai, N. (2018). *Do visual product reviews affect online shoppers' behavior? An empirical study of Chinese consumers.* Journal of Retailing and Consumer Services, Vol. 40, pp. 246-254.

Ye, Q., Law, R. and Gu, B. (2009). *The impact of online user reviews on hotel room sales.* International Journal of Hospitality Management, Vol. 28 (1), pp. 180-182.

Yi, N., Li, C., Feng, X. and Shi, M. (2017, November). *Design and implementation of movie recommender system based on graph database.* In 2017 14th Web Information Systems and Applications Conference (WISA), pp. 132-135. IEEE.

Yıldırım, A. (1999). *Nitel araştırma yöntemlerinin temel özellikleri ve eğitim araştırmalarındaki yeri ve önemi.* Eğitim ve Bilim, Vol. 23 (112).

Yu, D., Anser, M. K., Peng, M. Y. P., Nassani, A. A., Askar, S. E., Zaman, K., ... and Jabor, M. K. (2021, February). *Nationwide lockdown, population density, and financial distress brings inadequacy to manage COVID-19: leading the services sector into the trajectory of global depression.* In Healthcare, Vol. 9 (2), pp. 220. MDPI.

Yuan, Y. H., Tsao, S. H., Chyou, J. T. and Tsai, S. B. (2020). *An empirical study on effects of electronic word-of-mouth and Internet risk avoidance on purchase intention: from the perspective of big data.* Soft Computing, Vol. 24, pp. 5713-5728.

Yun, Y., Hooshyar, D., Jo, J. and Lim, H. (2018). *Developing a hybrid collaborative filtering recommendation system with opinion mining on purchase review.* Journal of Information Science, Vol. 44 (3), pp. 331-344.

Zhang, M. and Hurley, N. (2010). *The Role of Cognitive Theories in Recommender Systems.* In Recommender Systems Handbook, pp. 121-144. Springer.

Zhang, W., Du, Y., Yang, Y. and Yoshida, T. (2018). *DeRec: A data-driven approach to accurate recommendation with deep learning and weighted loss function.* Electronic Commerce Research and Applications, Vol. 31, pp. 12-23.

Zhang, Y., Zhang, J. and Sun, Y. (2015). *The impact of online reviews on product sales: A dynamic pricing problem.* European Journal of Operational Research, Vol. 244 (2), pp. 517-527.

Zhen, Z., Zhang, J. and Yu, Y. (2019). *A discrete choice experiment study of consumer preferences for online shopping in China.* Computers in Human Behavior, Vol. 94, pp. 160-168.

Zhou, T. and Lu, Y. (2011). *Examining mobile instant messaging user loyalty from the perspectives of network externalities and flow experience.* Computers in Human Behavior, Vol. 27 (2), pp. 883-889.

Zhu, F. and Zhang, X. (2010). *Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics.* Journal of marketing, Vol. 74 (2), pp. 133-148.

Zihayat, M., Ayanso, A., Zhao, X., Davoudi, H. and An, A. (2019). *A utility-based news recommendation system.* Decision support systems, Vol. 117, pp.14-27.

APPENDICES

Appendix A: Questionnaire

QUESTIONS OF INTERVIEW

1. Have you ever done online shopping before? How long have you been doing this? Has the pandemic increased your frequency of online shopping?
2. If so, how often do you shop online?
3. Which products do you usually prefer to shop online for?
4. Do you look at the recommender system when shopping?
5. Do you look at comments when searching for a product?
6. Have you ever changed your purchase decision or made a purchase decision based on comments?
7. Is the rating of comments important to you, or is the number of comments important, or both?
8. Are the comments of celebrities important to you? Does it affect your purchase decision?
9. According to what you evaluate the reliability of the comments? What factors tell you whether a comment is accurate or not? (For example, only those who buy that product can comment on Trendyol, maybe other platforms don't apply it.)
10. Do you pay attention to the phrase 'Bought this product' that appears next to the users' name in the comments, does it get your attention? Do you trust this phrase? Do you make a purchase decision accordingly or have you reviewed the product accordingly?
11. How many stars out of 5 does a product need to get to interest you? Has the number of stars ever changed your purchase decision?
12. Do you think there are differences between platforms? Which online marketplaces do you shop at?
13. Do you want products to be recommended based on your product history, or do you want products to be recommended based on the product history of other users who are looking at that product?
14. Do you trust the phrases 'Editor's choice', 'Celebrity's choice' on the products? Have you ever changed your purchase decision accordingly? Does this differ according to the product types?

Appendix B: Pilot Test Survey

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.4	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.4	3.5 - 4.4

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.4	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to my own product history
Number of comment	0 - 49	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.4	3.5 - 4.4

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	0 - 49	100 +
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	Above 4.5	3.5 - 4.4

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.4	3.5 - 4.4

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	Above 4.5	3.5 - 4.4

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Exist	Not exist
The comment with photo	Exist	Exist
The rating of product	Above 4.5	3.5 - 4.4

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.4	3.5 - 4.4

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	0 - 49	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.4	Above 4.5

Appendix C: Main Test Survey Preparation

Prior Mean

Effect	Prior Mean
The way the item is recommended	0,554
Number of comments 1	0,172
Number of comments 2	0,512
Influencer comments	0,658
The comment with photo	0,770
The rating of product 1	0,034
The rating of product 2	0,526

☐ Ignore prior variance. Generate the local design for the prior mean.

Prior Variance Matrix

Effect	The way the item is recommended	Number of comments 1	Number of comments 2	Influencer comments	The comment with photo	The rating of product 1	The rating of product 2
The way the item is recommended	0,0004951600000000000	0,000	0,000	0,000	0,000	0,000	0,000
Number of comments 1		0,000	0,000	0,000	0,000	0,000	0,000
Number of comments 2			0,001	0,000	0,000	0,000	0,000
Influencer comments				0,000	0,000	0,000	0,000
The comment with photo					0,000	0,000	0,000
The rating of product 1						0,000	0,000
The rating of product 2							0,000

Design Generation

5	Number of attributes that can change within a choice set
2	Number of profiles per choice set
10	Number of choice sets per survey
5	Number of surveys
100	Expected number of respondents per survey

Appendix D: Main Test Survey

Survey 1.

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.49	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Exist	Not exist
The rating of product	3.5 - 4.49	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	0 - 49	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	3.5 - 4.49	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	2.5 - 3.49

Survey 2.

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	3.5 - 4.49	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	3.5 - 4.49	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	0 - 49
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	2.5 - 3.49

Survey 3.

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	0 - 49
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	3.5 - 4.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	100 +
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	Above 4.5	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	0 - 49	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	3.5 - 4.49	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	0 - 49	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	100 +
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	0 - 49
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	100 +
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	2.5 - 3.49

Survey 4.

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	0 - 49
Influencer comments	Exist	Not exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	0 - 49
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	Above 4.5	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	0 - 49
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.49	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	0 - 49
Influencer comments	Exist	Not exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	0 - 49	100 +
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	Above 4.5

Survey 5.

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.49	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	100 +	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	3.5 - 4.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	0 - 49	100 +
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	50 - 99	0 - 49
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	0 - 49	50 - 99
Influencer comments	Exist	Not exist
The comment with photo	Exist	Not exist
The rating of product	2.5 - 3.49	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	100 +
Influencer comments	Not exist	Exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	50 - 99
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	2.5 - 3.49

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	100 +	0 - 49
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	2.5 - 3.49	3.5 - 4.49

	Scenario 1	Scenario 2
The way the item is recommended	According to the product history of other users	According to my own product history
Number of comment	50 - 99	100 +
Influencer comments	Exist	Not exist
The comment with photo	Not exist	Exist
The rating of product	3.5 - 4.49	Above 4.5

	Scenario 1	Scenario 2
The way the item is recommended	According to my own product history	According to the product history of other users
Number of comment	0 - 49	100 +
Influencer comments	Not exist	Exist
The comment with photo	Exist	Not exist
The rating of product	Above 4.5	3.5 - 4.49