DO SPECIFIC PERSONALIZED RECOMMENDATIONS CAUSE MORE HARM THAN GOOD TO SOCIAL IDENTITY? A MODERATED MEDIATION MODEL.

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ABSTRACT

This dissertation investigates how personalized product recommendations—whether from human or artificial intelligence recommenders (AI-R)—can unintentionally trigger adverse psychological reactions such as social identity threats, particularly when the product or its presentation is associated with dissociative reference groups. The scope of this research explores the influence of the signaling content of a reference group (associative vs. dissociative), the recommender type (AI vs. humans), and identifying moderators such as collective self-esteem (CSE), stereotype-related fear of negative evaluation (SR-FNE), and the possibility of price discounts overriding identity threat concerns and perceived price (PP) that shape consumers' reactions.

A pretest and two studies with 510 participants from a diverse Turkish sample showed that even accurate product recommendations can lead to negative feelings when the product is linked to a group from which someone wants to dissociate. While the recommender type (H1) did not yield a significant main effect, subgroup analyses revealed differential responses based on age and gender.

A significant effect was found for reference group imagery (H2): dissociative visuals led to lower product liking and higher SIT, supporting H3's mediation model. PROCESS Model 4 confirmed SIT as a significant mediator in the relationship between visual cues and consumer response. Further, PROCESS Models 1 and 14 demonstrated that CSE marginally moderated the effect of reference group type on SIT_DC, while SR-FNE did not significantly moderate the indirect path.

Hypothesis H7 tested a three-way interaction (PROCESS Model 18); CSE and SR-FNE did not consistently moderate these effects, although partial effects were observed in specific recommendation contexts. Further, three-way interactions involving SIT_DC, SR-FNE, and PP, H8 (tested via PROCESS Model 37), showed that limited but suggestive evidence that identity threats have stronger negative impacts when consumers are highly sensitive to social evaluation and perceive higher prices.

Overall, the results highlight the importance of social-psychological cues in shaping consumer reactions to recommendation systems. This research contributes to the marketing and human–AI interaction literature by demonstrating that even accurate recommendations may backfire if they evoke identity threats or fears of stereotyping, especially when consumers are highly evaluative or perceive the product as high-value.

Keywords: AI vs Human Recommenders; Personalized Product Recommendations; Social Identity Threat; Collective Self-Esteem; Dissociative Reference Groups

ÖZ

Bu tez, kişiselleştirilmiş ürün önerilerinin (ister insan ister yapay zekâ tavsiye edicilerinden olsun) sosyal kimlik tehditleri gibi istenmeyen psikolojik tepkileri, özellikle de ürün veya sunumu disosiyatif referans gruplarıyla ilişkilendirildiğinde, nasıl tetikleyebileceğini araştırmaktadır. Bu araştırmanın kapsamı, bir referans grubunun sinyal içeriğinin (asosiyatif veya disosiyatif), tavsiye eden türünün (YZ veya insanlar) etkisini ve kolektif öz saygı (CSE), olumsuz değerlendirmeye ilişkin stereotiple ilişkili korku (SR-FNE) ve fiyat indirimlerinin kimlik tehdidi endişelerini ve tüketicilerin tepkilerini şekillendiren algılanan fiyatı (PP) geçersiz kılma olasılığını araştırmaktadır.

Çeşitli bir Türk örnekleminden 510 katılımcıyla yapılan bir ön test ve iki çalışma, doğru ürün önerilerinin bile, ürün birinin disosiyatif referans gruplarıyla ilişkilendirildiğinde olumsuz duygulara yol açabileceğini göstermiştir. Tavsiye eden türü (H1) önemli bir ana etki üretmezken, alt grup analizleri yaşa ve cinsiyete göre farklı tepkiler ortaya koymuştur.

Referans grup imgelemesi (H2) için önemli bir etki bulundu: ayrışmış görseller daha düşük ürün beğenisine ve daha yüksek sosyal kimlik tehdidine (SIT) yol açtı ve H3'ün aracılık modelini destekledi. PROCESS Model 4, sosyal kimlik tehdidinin görsel ipuçları ile tüketici tepkisi arasındaki ilişkide önemli bir aracı olduğunu doğruladı. Dahası, PROCESS Modelleri 1 ve 14, kolektif öz saygının (CSE) referans grup tipinin sosyal kimlik tehdidi (SIT) üzerindeki etkisini marjinal olarak düzenlediğini, stereotipe bağlı olumsuz değerlendirme korkusunun (SR-FNE) ise dolaylı yolu önemli ölçüde düzenlemediğini gösterdi.

Hipotez H7, üç yönlü bir etkileşimi test etti (PROCESS Model 18); kolektif öz saygı ve olumsuz değerlendirme korkusu bu etkileri tutarlı bir şekilde düzenlemedi, ancak belirli öneri bağlamlarında kısmi etkiler gözlemlendi. Dahası, sosyal kimlik tehdidi, SR-FNE ve algılanan fiyat, H8'i içeren üç yönlü etkileşimler (PROCESS Model 37 ile test edildi), tüketicilerin sosyal değerlendirmeye karşı oldukça hassas oldukları ve daha yüksek fiyatlar algıladıkları durumlarda kimlik tehditlerinin daha güçlü olumsuz etkilere sahip olduğuna dair sınırlı ancak düşündürücü kanıtlar gösterdi. Genel olarak, sonuçlar, tüketicilerin öneri sistemlerine tepkilerini şekillendirmede sosyal-psikolojik ipuçlarının önemini vurgulamaktadır. Bu araştırma, özellikle tüketiciler son derece değerlendirici olduğunda veya ürünü yüksek değerli olarak algıladığında, kimlik tehditleri veya stereo tipleme korkuları uyandırırsa, doğru önerilerin bile ters tepebileceğini göstererek pazarlama ve insan-AI etkileşim literatürüne katkıda bulunmaktadır.

Anahtar Kelimeler: Yapay Zekâ ve İnsan Önericiler; Kişiselleştirilmiş Ürün Önerileri, Sosyal Kimlik Tehdidi; Kolektif Benlik Saygısı, Dissosiyatif Referans Grupları

To N.E.S.

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Dr. Burcu Selcan

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LIST OF ABBREVIATIONS

AI: Artificial Intelligence

AI-R: AI Recommenders

AI-RS: AI based Recommender Systems

ANCOVA: Analysis of Covariance

ANOVA: Analysis of Variance

CSES: Collective Self-Esteem Scale

FNE: Fear of Negative Evaluation

H-RE: Human Recommenders

HCI: Human-computer interaction

SIT_DC: Social Identity Threat & Dissociative Concerns

SIThr: Social Identity Threat

SR-FNE: Stereotype Related Fear of Negative Evaluation

There it was: The Self Hell aisle.
As Charlotte looked at the titles: The Woman's Comfort Book, The Path to Love, Excuse Me, Your Life is Waiting, Please Understand Me II, she couldn't bear the thought that she belonged there.
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You've got mail.
"Based on your recent book purchase, here's a list you might be interested in."
The selected list included: Lonely Women No Men, Love Hurts, You Don't Have to, I'm Fine Now, and Reservations for One. Charlotte refused to see herself as one of those type of women.
Sex and the City S5 E4 (2002)

INTRODUCTION

The attitudes of consumers are changing alongside the advancement of technology (Tiwari 2019; Johnson, Purwanegara, and Mulyono 2024a). Instead of shopping from brick-and-mortar stores, customers prefer to purchase online through e-commerce or social media platforms (Marinšek et al. 2018); alternatively, instead of going to a movie in a theater, video-on-demand content streaming platforms such as Netflix or Prime Video are preferred ("Survey: US Viewers Prefer Streaming Movies over Cinema | Advanced Television" 2025). Finally, consumers prefer mood-based playlists on music-on-demand services like Spotify compared to traditional radio (Leu 2024). All the examples discussed share a commonality that their business structures are founded on recommendation systems (Gai and Klesse 2019). What drives the popularity and preference for recommendation systems?

Individuals tend to rely on other individuals' recommendations in every single aspect of their lives (Resnick and Varian 1997) due to the reason that those recommendations will help them during the decision-making process (Ladesma 2020; Pathak et al. 2010). With the rapid developments in this digital age, where hyper-competition creates an overwhelming number of alternatives, this tendency shifts from human to artificial intelligence (henceforth AI), from word of mouth to word of the machine (Longoni and Cian 2020). In other words, this shift results from hyper-competition, which has overstimulated consumers with too much information and a vast number of products or services. This made it difficult for customers to choose from unlimited options. Because of their limited ability to cognitively grasp information and because it is impractical for customers to weigh all options before choosing one, consumers are left with no choice but to filter and narrow down choices or opt for AI-based algorithmic systems (chatbots, marketing automation tools, recommender engines, retargeting tools, etc.) for supporting their decision-making process (Farhoomand and Drury 2002; Ladesma 2020; Pathak et al. 2010). In a world where AI-based or algorithmic-based recommendations help consumers simplify their complex decision-making processes and where recommendation systems are a result—or, in some cases, the response—of the desire to customize and personalize to feel special, this context naturally led to AI vs. human comparisons in terms of which one is a better recommender or advisor.

While the recommendation is a particularly effective decision support system for consumers, there are certain disadvantages associated with it. In general, the most prominent disadvantages are the possibility of algorithm failure (Dietvorst, Simmons, and Massey 2015; Srinivasan and Sarial-Abi 2021; Castelo, Bos, and Lehmann 2019; Daschner and Obermaier 2022; C. Chen 2024), the filter bubble effect or information cocoons—an invisible circle around everyone because of personalization algorithms and being unaware of other options—in algorithmic culture (Nguyen et al. 2014; Pariser 2011; Sihua Chen et al. 2022) last but not least, privacy concerns (Chellappa and Sin 2005; H. T. Chen 2018; Lohuizen 2021; Tomaino, Wertenbroch, and Walters 2021; Almuhimedi et al. 2014; Barev, Schwede, and Janson 2021). But what if there is another significant disadvantage that has not surfaced yet?

The literature on AI vs. human comparisons has expanded significantly over the past two decades across disciplines, including human resource management (HRM), finance, healthcare, consumer studies, and human-computer interaction (HCI). However, studies examining recommender systems, particularly comparing human and AI recommenders, have been relatively limited within this expanding literature. More specifically, in the marketing field, there are few publications addressing AI and Human Recommender (henceforth H-RE). On the other hand, while there are increasing studies examining adverse customer reactions in the context of algorithmic culture, recommendation, and personalization, the literature on the negative attitudes of a customer towards a recommended product is still limited.

1.1 Problem Definitions

While it is suggested that individuals who recognize and are confident in their needs are more likely to adhere to AI recommendations (Y. Zhu et al. 2022), are there other circumstances in which they might behave differently? This dissertation assumes that, in some cases, even if consumers are aware of their needs and have done preliminary research to meet them, they may exhibit a negative attitude when they receive a recommendation regarding this identified need. The question is: under what circumstances do potential customers feel uncomfortable, even irritated, regarding this personalized recommendation, even though it meets their needs accurately? Is it related to the type of recommended product (a product that may be deemed private, intimate, or even taboo by potential customers, even if not for others)? Is it related to the type of recommender (human vs. AI)? Is it related to what the product/service or brand represents (e.g., an association with a dissociative reference group), or is it associated with the concept of personalization itself? When it comes to personalized product recommendations, what triggers negative responses?

1.2 Purpose of the Study

To address this problem and shed light on this uncharted region, it is crucial to investigate and try to comprehend the situations in which customers would react to personalized recommendations. Numerous scenarios could lead to adverse customer responses, given that various unpredictable factors influence consumer behavior. Consumers might respond unfavorably to one recommender and favorably to another, or even if the customer has a negative attitude towards both types of recommenders (human vs. AI), the extent of the consumer's reaction may be greater depending on the recommender. This dissertation aims to explore the motivations behind consumer reactions to recommender types and personalized recommendations, as well as to fill the gap in the literature on identifying moderators that shape customers' reactions by contributing to the limited number of studies on human vs. AI recommenders in the marketing field. In addition, this dissertation aims to contribute to the literature by examining the impact of the signaling content of a recommendation, particularly its implication of a connection to a dissociative reference group, on adverse consumer reactions, even when they receive a needed or desirable recommendation. Finally, this dissertation will seek to determine whether AI-based recommenders (henceforth AI-R) trigger the fear of labeling and stereotyping, depending on the recommendation, by expanding the literature on AI vs. H-RE.

As a result of the information that has been stated so far, in a world where there are no adverse situations (no algorithmic aversion, no algorithmic errors, no filter bubble effect, etc.) and both human and AI-R have the same ability to predict or recommend what consumers need or desire accurately, this research aims to focus on answering the following question. The main research question is, *even if a product is recommended that is precisely what the consumer is looking for or needs, can the consumer's reaction differ depending on whether the recommended product evokes or symbolizes a dissociative reference group, and does this reaction differ depending on whether the recommendation comes from H-RE or AI-R?*

1.3 Significance of the Research

This research question is significant for comprehending the effects of AI-based recommendation systems (henceforth AI-RS) on consumer perceptions for academic research and marketing applications. Modern marketing strategies revolve around the assumption that personalization strengthens consumer experience and that tailored recommendations aligning with consumer wants and needs are consistently received favorably (Abbas 2024; Hyken 2024). However, this dissertation challenges this assumption and suggests that personalization can backfire in specific contexts and trigger unexpected negative emotions in consumers (Bhattacharjee, Berger, and Menon 2014; Cohn 2016; J. Li et al. 2020; Byrne and Milestone 2022; Wrobel 2002). Investigating how consumers react to personalized recommendations is essential to fill gaps in the literature and provide critical insights for designing more effective and ethical recommendation systems.

While these systems are designed to enhance personalization and improve user experience, their unintended consequences remain underexplored (Adomavicius et al. 2018; Pappalardo et al. 2024; Ma, Huang, and Dennis 2024). This dissertation examines whether AI-generated recommendations, despite being highly personalized and accurate, can lead to negative consumer responses, particularly when the recommended product is associated with a dissociative reference group (K. White and Dahl 2006; Dunn, White, and Dahl 2013). By doing so, this dissertation challenges the prevailing assumption in marketing that personalization almost always enhances consumer satisfaction (Shang et al. 2023; C. Li 2024) and contributes to the literature that, in some cases, accurate personalization can generate negative sentiment (Mallek, Bawack, and Bonhoure 2024; De Freitas et al. 2025).In addition, recent discussions on AI ethics also highlight the risks of algorithmic decision-making (Wylde et al. 2023; Hajian, Bonchi, and Castillo 2016; De Cremer and Kasparov 2021; J. Metz 2021; Azer et al. 2023), emphasizing the need for businesses to anticipate and address potential negative consequences proactively.

The majority of the existing literature primarily focuses on system performance, recommendation accuracy, and consumer preference for AI versus human recommendations. However, this research takes a different approach by investigating how personalization, under specific conditions, can trigger identity threats and negative emotional responses, not only toward the recommendation itself but also toward the entity making it. Specifically, this dissertation addresses this gap by examining how the source of the recommendation (AI vs. human) and the perceived association with dissociative reference groups influence consumer responses.

1.4 Structure of the Dissertation

By addressing this gap, the dissertation offers theoretical contributions to consumer behavior literature and practical insights for companies aiming to refine their recommendation strategies. The findings will inform future research on consumer reactions such as purchase intentions, negative attitudes toward recommendations, word-of-mouth marketing, algorithm avoidance, and even AI phobia (Kim, 2019, 14). From a managerial perspective, this dissertation offers valuable insights on how businesses can design recommendation systems that enhance personalization while minimizing perceived irritation (Hasan 2016), providing insights into the psychological mechanisms underlying consumer responses to personalized recommendations, ultimately contributing to a more ethical and practical application of AI in marketing.

To address the question, this dissertation is organized as follows: The Theoretical Background section will analyze researchers' general attitudes across various academic fields regarding recommendations and recommendation systems, compare AI-R with H-RE in the literature, and explore consumers' perceptions of recommendations from both AI and H-RE. Then, the impact of the reference groups symbolized by the content of the recommended product on the consumer's social identity (K. White and Argo 2007) and how threats to this identity shape consumer attitudes will be discussed. Finally, how variables such as collective self-esteem (Luhtanen& Crocker, 1992), fear of negative evaluation (Leary 1983) based on stereotyping, and perceived price (Dodds, Monroe, and Grewal 1991) play a role in this process will be investigated. This section aims to strengthen the theoretical foundation of the dissertation by examining the existing literature.

Next, the Methodology section will provide details of the factorial design, sample characteristics of the participants, data collection procedures, and data analysis methods applied in the research. In addition, this section will cover the translation, back-translation, and cross-cultural adaptation process of translated scales (Yasir 2016).

The Hypotheses, Results, and Research Findings section will present empirical results, focusing on participants' responses to whether personalized recommendations vary according to the recommended product's reference group (associative vs. dissociative) and recommender type (AI vs. human). The General Discussion section covers theoretical and managerial implications and interprets the findings in the context of consumer behavior, marketing strategies, and recommendation system development. In addition, this section provides this dissertation's contributions and limitations, as well as recommendations for future research.

Finally, the conclusion section will summarize the key findings, emphasize the dissertation's contributions to the literature, and present the overall implications of the research.

In this context, the following section briefly summarizes the existing literature on AI vs. H-RE, highlighting studies on human-based vs. AI-based advice-taking and consumer trust in algorithmic recommendations.

THEORETICAL BACKGROUND

2.1 Consumer Decision Making

2.1.1 The Consumer Decision-Making Process

People, from minors to seniors, have exceedingly many decisions to make every day in countless different areas despite the uncertainty surrounding future events. While some decisions are regarding dramatic, life-changing situations such as having a Ph.D. degree or studying abroad, others are about simply considering carrying an umbrella or buying a generic toilet paper for the first time.

When consumers are torn between options, they must make a purchase decision, and according to the Cambridge Dictionary, the word decide means “to choose something, especially after thinking carefully about several possibilities.” So, consumer decision-making can be defined as the cognitive process of a course of action regarding purchase decisions from various potential alternatives. Regardless of whether the purchase decisions are rational or irrational (emotional), the primary objective of the decision-making process is to resolve a problem or issue (Hansen 1976). In other words, as John Dewey defines it, the consumer decision-making process starts with a purchase that is a response to the problem.

From a marketing perspective, Dewey’s five-stage model can be stated as the first model for the decision-making process (Bruner 1988). This process can be categorized as problem recognition/identification, information search, evaluation of alternatives, product choice, and post-purchase evaluation. Apart from the 5-stage model, which is also known as the problem-solving model, other important models have been presented since 1960, such as the AIDA (awareness, interest, desire, action) model, the hierarchy of effects model, and the innovation acceptance model. But, when each model is examined one by one, it is seen that there are similar approaches and that all models begin the decision-making process by either recognizing the problem or drawing attention to it

(Hoyer & MacInnis, 2008, 195; Solomon et al., 2016, 331). The following stages reveal a tendency to browse information about products or services to solve this problem or meet the need. At this browsing stage, the cognitive process comes into play, and the consumers start to research and collect information about the product or service they want to purchase. After the evaluation phase, the purchase decision is made. The final stages are more concerned with evaluating purchased and used products. When the evaluation is positive, purchasing the same product and brand continues; in case of dissatisfaction, there is a tendency to substitute goods (Kotler et al., 2016, 174).

While decision-making stages remain relatively consistent across models, what has significantly changed over time is how consumers access and process overloaded information, particularly at the information search and evaluation phases. In the past, people obtained information from friends, television, radio, and newspapers to evaluate their buying decisions (Hoyer & MacInnis, 2008, 205; Solomon et al., 2016, 336). Today, the needs and attitudes still stand, but with information overstimulation, the medium of the information has evolved. While people still prefer peer or expert opinions when evaluating products or services (depending on the nature of the purchase) (J. Wang, Molina, and Sundar 2020; Dai, Chan, and Mogilner 2019) and continue to obtain information through media channels, now the internet and AI-RS play a crucial role in providing consumers with necessary information (Hinz and Eckert 2010; Ricci, Rokach, and Shapira 2011; Gai and Klesse 2019). What could be the underlying reason for this phenomenon?

2.1.2 AI-Supported Decision Making

In today's digital ecosystem, people increasingly rely on AI-RS to enhance their decision-making processes, whether the task involves choosing driving routes, selecting leisure activities, formulating investment strategies, or navigating legal procedures (Liel and Zalmanson 2023). The accuracy and uncertainty reduction effect of AI-powered decisions reinforces consumers' trust in these systems (X. Wang, Lu, and Yin 2022). It leads people to perceive AI not only as a supporting tool but also as a "companion" in their relationships and decision-making processes (Chaturvedi et al. 2024). However, alongside its benefits, this increased trust has led to new problems such as an automation bias (blindly trusting outputs) (Darioshi and Lahav 2021) or over-reliance on AI-supported decision-making (Lu, Wang, and Yin 2024) that raises concerns about freedom of consumer choice, autonomy (André et al. 2018) and ethical discomfort (Kasinidou et al. 2021). However, this over-reliance does not arise in all contexts. For example, consumers rely more on external sources of information, such as reviews and AI recommendations, when purchasing tangible goods than experiential goods (Dai, Chan, and Mogilner 2019). This finding suggests that the nature of the decision can moderate the impact of algorithmic inputs.

The nature of the consumer's problem, or the extent of need, determines how decision-support systems will be used and how much they will rely on AI. It is also an important indicator of how fast the decision process will be taken, how much cognitive effort will be devoted, and how much trust will be placed in the recommender. For instance, in limited problem-solving situations, consumers use cognitive shortcuts when making decisions and spend very little time on the research process; in this context, the use of recommendation systems can positively affect customer satisfaction. On the other hand, perceived risk is higher in product purchase decisions that require intensive problem-solving, and consumers need to seek additional research and advice from peers or experts in this case (Solomon et al., 2016, 354). Fan and Liu (2022) state that consumers develop an inherent trust in the system when the decision-making process is automated, which, as a result, increases dependence. Similarly, Morosan and Dursun-Cengizci (2023) suggest that user-friendly AI interfaces can encourage consumers to completely delegate their decisions, especially in situations where efficiency is a priority. However, excessive reliance can lead to decreased decision quality and increased risk of error (Sele and Chugunova 2022). Therefore, to reduce the risks, Wang et al.(X. Wang, Lu, and Yin 2022) suggest that providing second opinions from alternative AI sources or human experts can reduce over-reliance and provide a more balanced decision environment. Especially in cases where AI recommendations conflict with the consumers' identities or preferences, the involvement of second opinions plays a critical role in increasing consumer trust (Fan and Liu 2022; Laban Guy and Araujo Theo 2020). In this context, although fully automated systems can provide higher accuracy, users generally prefer hybrid systems with human intervention where the perceived risk is high; therefore, the need for support from peers or experts is greater.

Although seeking a second opinion from experts is still essential when making high-stakes decisions like financial or medical decisions (X. Wang, Lu, and Yin 2022; Fan and Liu 2022; Chua, Pal, and Banerjee 2023), recommendation systems have become vital tools for handling excessive amounts of information and assisting in decision-making in low-risk situations like online shopping, where consumers are confronted with an infinite number of options (Flaswinkel and Decker 2024; Farhoomand and Drury 2002; Lurie et al. 2018)

To conclude, what has been stated so far regarding consumer decision-making processes and problem-solving to evaluate alternative stages is that in 1910, when this model was developed, or even in the 1990s, when there was a limited number of options, it was easy to evaluate all the possible alternatives within bounded rationality (Simon, 1957 quoted in Erez & Reyna, 2019). However, today, in the hypercompetitive digital world we live in, there is information and a vast amount of options stimulation (Flaswinkel and Decker 2024; X. Li et al. 2024), and it is almost impossible to do the second and third stages of the consumer decision-making process. This is because consumers have a limited cognitive capacity to process information (Payne, 1982). In other words, it is impractical for consumers to consider all options before choosing one. Customers have no choice but to filter and exclude information, use AI-RS or algorithm-based recommendation tools (Farhoomand & Drury, 2002), or recommender agents to save some cognitive work and help accelerate and improve the decision-making process when they are exposed to abundant choices (Darioshi & Lahav, 2021). In addition, personalization is important in recommendations since it has a key role in providing a positive experience for the consumer in terms of tailoring the experience to the user's individual preferences and needs (B. Zhang & Sundar, 2019).

In the following sections, recommended systems and the concept of recommendation will be briefly covered under the context of customer decision-making. After that, the concept of personalization and why it is important for recommendations is briefly explained.

2.1.3 Concept of Recommendations & Recommender Systems

In its simplest definition, a recommendation, whether it comes from a person or a system, is the ability to predict if a customer will prefer a product or service based on their behavior, preferences, and past choices (Gao et al., 2021; Johnson et al., 2024b). As is their nature, humans rely on their peers, opinion leaders, and experts' recommendations in their daily lives (D'Angelo & Valsesia, 2022; Resnick & Varian, 1997; Wien & Peluso, 2021). From a movie or a book recommendation to a product or a service, recommendations help consumers deal with excessive choices. Even from an academic point of view, to be accepted for a program, candidates should provide recommendation letters from their lecturers (Ricci et al., 2011). Regardless of the use area, it reduces search costs and time consumption (Hinz & Eckert, 2010; Ladesma, 2020; Pathak et al., 2010; Yang et al., 2024). On the other hand, recommendation systems are based on machine learning algorithms to primarily assist individuals in making wise choices and decisions (Jameson et al., 2015), which seek to "learn" a consumer's preferences based on their previous actions and then use that knowledge to suggest new products or services (Ricci et al., 2011) from a vast of options (Huseynov et al., 2014).

The reason for the shift to new platforms with recommendation systems in customer behavior can be attributed to the fact that, with the increase in product and service alternatives, and therefore a substantial number of possibilities, it is difficult for consumers to choose the right options for themselves (Yoon and Lee 2021), since especially indecisive shoppers spend most of their time searching, reviewing, comparing, and choosing (Kim, 2020) from abundant options. This hinders the enjoyment of shopping or services. At this point, the recommendation systems not only improve decision-making processes by preventing time loss for customers and helping customers discover the latest items that they were not aware of but also reduce transaction costs from a platform perspective (Isinkaye et al., 2015; Özgöbek & Erdur, 2015). The only question is, under which circumstances do consumers prefer a human agent over an AI agent (or vice versa) as a recommender or an advice giver? This is one of the crucial questions the academic circle focuses on and conducts studies to answer in different domains and variables.

Although when the recommendation systems literature is examined, there are numerous studies in the field of technical infrastructure, performance, efficiency, and application (Deng & Kahn, 2009; Gai & Klesse, 2019; Hinz & Eckert, 2010; Hu et al., 2018; Isinkaye et al., 2015; Komiak & Benbasat, 2006; S. S. Li & Karahanna, 2015; Michels et al., 2022), and growing studies regarding H-RE vs. AI-R, as it was stated before; still relatively limited studies focus on the psychological inputs of consumers' decision-making process (Jameson et al., 2015) and reactions to recommendations and recommenders (De Freitas et al., 2023; Wien & Peluso, 2021; Yalcin et al., 2022). In fact, according to the literature review conducted so far, no prior research has focused on the causes of a negative attitude toward a personalized recommendation, even if the recommended product is the one the consumer is looking for. This dissertation aims to contribute to the literature by filling this gap with the assumption that while recommendations are helpful and facilitate the consumer's well-being, even in a perfectly designed marketing world, it might be challenging to foresee some adverse circumstances. To grasp the significance of AI-driven RS's value and limitations, it is essential to understand the concept of "personalization" itself. The following section will explore the significant impact of personalization in the context of product recommendations within recommendation systems (Habil et al., 2023).

2.1.4 The Effect of Personalization & Personalized Recommendations

According to the Cambridge Dictionary, personalization is "the act of making something suitable for the needs of a particular person," yet in academic literature, this term has been provided with distinct definitions by various researchers when conceptualizing it (Chandra et al., 2022). While some scholars define it as a business strategy (Arora et al., 2008; E. Y. Huang & Lin, 2005) or firm capability (Berg et al., 2001; Chellappa & Sin, 2005), others view it as a process (Blom & Monk, 2003; Murthi & Sarkar, 2003). From a broader perspective, Sunikka and Bragge (2012) defined personalization as a customer-focused marketing strategy aiming to optimize business opportunities by delivering "the right product/service/experience to the right person at the right time and the right place."

Grounded in relationship marketing, personalization (Crosby et al., 1990; Dwyer et al., 1987; quoted in Sunikka & Bragge, 2012) dates back to the late nineteenth century, when salespeople in local stores knew customers by name, knew their regular orders, and could enhance the customer experience by truly understanding their customers' needs and wants (Alexander, 2020; Ross, 1992), long before online shopping and recommendation systems (Shen & Dwayne Ball, 2009). Since then, personalization has evolved with the rise of digitalization and new technologies. In this transformation process, businesses have met the need to handle personalized consumer requests and expectations beyond their control (Kostow, 2021; Venkatraman, 2017) and have transformed into data-driven strategies in order to maintain a competitive advantage in this hyper-competitive modern market (Ansari & Mela, 2003; Weill & Woerner, 2018; quoted in Borges et al., 2021). Thus, personalization has become a fundamental element of consumer experience and engagement. In other words, personalization has evolved from human-to-human interaction to data-driven, AI-based interaction. This new structure customizes products, services, or even experiences using various strategies, including collaborative filtering, content-based filtering (Ansari et al., 2000), and demographic-based targeting based on user-specific attributes or preferences (Blut et al., 2023; Hayes et al., 2021), and has become a fundamental element of consumer engagement (Abbas, 2024).

In today's AI-driven, hyper-connected, and hyper-competitive digital world, where consumers have a shorter attention span (Kotler et al., 2016, 59) with a vast amount of stimulation, countless companies are using personalization applications to leverage consumer data and influence shopping decisions (Gökdemir & Akıncı, 2019) in both brick-and-mortar and online platforms (Aguirre et al., 2014). It can be suggested that the reason for this necessary increase in personalization efforts is to capture the attention of customers in a world where they are exposed to abundant options to offer products, services, or experiences that are relevant to their past behaviors and needs, to achieve marketing efficiency, and to build long-term relationships, as research shows that

(Batistão, 2024) 76% of customers now expect personalization from companies. Therefore, companies often implement personalization, primarily through algorithm-based or AI-based systems, such as recommendation systems (AI-RS), to improve the recommendation experience for users who expect a hyper-relevant experience. In a world where expectations are this high and customers are unhappy without personalization (Arora et al., 2021), recommendation systems, or the recommendation experience in general, should not be considered without personalization.

Indeed, the literature provides strong support for the effectiveness of personalized recommendations. Studies have shown that these tailor-made interactions that offer items or materials that appeal to users' interests and preferences can significantly increase consumer engagement, loyalty, and purchase intentions (Habil et al., 2023; Hayes et al., 2021; Martínez-González & Álvarez-Albelo, 2021; K. T. Smith, 2019). AI-RS was built to serve as a tool to gather and analyze data on consumers' preferences and profiles to deliver effective personalized messages, identify the right customer at the right time, and allocate marketing efforts more efficiently (Leblebici Koçer & Özmerdivanli, 2019). Personalized messages are often perceived as more helpful and proactive, especially when they reflect the customer's unique preferences or needs. (Otterbring et al., 2023)Therefore, digitalized systems (i.e., AI-based systems) are significantly enhancing a firm is not only marketing and sales but also other efforts such as customer experience management, strategic management, supply chain, and finance by streamlining business processes, facilitating real-time optimizations, and enhancing predictions(Townson, 2021). This is due to excessive daily repetitive tasks, greater data preparation, initiation processes, and onboarding and acquisition costs (Cannone, 2021).

Despite the intended usefulness of personalized recommendations, recent studies have begun to reveal a more complex picture and raise questions (Koo, 2022; C. Li, 2024; Shen & Dwayne Ball, 2009). Could these hyper-relevant personalized recommendations be genuinely practical, or might they be perceived as intrusive in certain situations or by some individuals? Could users feel reduced to a particular stereotype or group based on the content of the recommendation, even if the recommended product is objectively relevant? Moreover, does the reaction toward recommendations differ depending on the type of recommender? Do customers tend to create more negative attitudes toward AI recommenders than humans due to the reason that hyper-personalization may cause concerns such as labeling, stereotype threat, and discrimination (Cohn, 2016; C. Metz, 2019)? In other words, is it because they see AI-RS as computerized stereotyping? The following section will examine the first AI vs. human literature to find an answer to these questions.

2.2 AI vs Human in Personalized Recommendation and Decision-Making

Over the past twenty years, the body of literature on AI vs. humans has grown under various disciplines, from medical care to recruitment. While some emphasize algorithmic authority and trust in them (Bauer, von Zahn, and Hinz 2023; Jussupow, Benbasat, and Heinzl 2020; Yuan, Zhang, and Wang 2022), others focus on algorithmic aversion and how algorithmic errors might lead to avoidance (Dietvorst, Simmons, and Massey 2015; Castelo, Bos, and Lehmann 2019; Daschner and Obermaier 2022; Filiz et al. 2021; Jussupow, Benbasat, and Heinzl 2020; B. Berger et al. 2021; Morewedge 2022; Reich, Kaju, and Maglio 2023; Castelo 2023).

Nevertheless, studies still show that despite the outperformance of AI-RS, or AI-R, over H-RE in various cases and AI's capability to encourage behavioral intention just as effectively as humans can (G. Huang and Wang 2023), people still tend to choose H-RE over AI (Önkal et al. 2009; Waytz and Norton 2014; Wien and Peluso 2021; Yiran Zhang, Tan, and Lee 2024; Shao et al. 2025). So, why can't we still give up on H-RE in some cases, even if AI-RS appears to be more efficient?

2.2.1 AI vs Human Performance Across Studies

To give examples regarding the recent contributions in different domains, such as healthcare, several research studies demonstrated that AI performs better than humans in diagnosing diseases such as sleep apnea (Thorey et al., 2019) or cancer (Hunter et al., 2022). However, other evidence reveals that patients still prefer human doctors over AI agents when diagnosing to avoid misdiagnosis. After all, AI might miss a special/one-of-a-kind circumstance (Longoni et al., 2019). Another reason for preferring human doctors is that AI agents cannot individuate patients (J. Chen et al., 2021). So, as can be seen, even when diagnosing a disease, the results can vary depending on the context.

Considering recruitment and candidate selection, people still prefer humans (versus AI agents) as human assessments are more fair, flexible, and helpful (Diab et al., 2011). Although one study shows that, depending on the nature of the job, AI can be accepted as a decision-maker or an evaluator (Waytz & Norton, 2014) still, another recent study supports the notion that—even though some respondents find AI more bias-free—people prefer to communicate with other human beings in the interview stage. If a firm utilizes AI during the interview stage, it will have a negative impact on how appealing organizations are perceived and how likely applicants are to apply (Wesche& Sonderegger, 2021).

Finally, to take a look at all the contributions in other fields, the latest research on AI vs. human comparison is full of empirical studies in everything from the creation of news headlines and how participants rated AI-generated news headlines as less accurate even though those were highly accurate (Longoni, Pennycook, et al., 2022) to teammate performance in the context of HCI and how humans accept the decisions of their AI partner more frequently because they behaviorally trust the AI more than another person (Y. Zhang et al., 2023), from bargaining behavior as the majority of respondents want to negotiate a contract with autonomous agents rather than the algorithm and demand greater remuneration (Erlei et al., 2022), to the structure of the organization and performance assessment showing algorithmic recommendations have considerable persuasive power (Liel & Zalmanson, 2021). One of the most recent articles on this argument is themed "AI-generated vs. human artworks," and it is worth mentioning the findings indicating a bias in favor of human systems and an unfavorable impression of AI (Ragot et al., 2020).

Although the literature on the AI vs. human comparison is a fascinating and growing topic, as was stated before, there is relatively limited literature on recommender systems or recommendations. Furthermore, there are hardly any publications about the marketing field when looking at these few studies comparing AI vs. H-RE, which leads to several gaps and development areas in the literature. Table 2.1 summarizes the results of recent empirical studies on AI vs. humans in the marketing domain. As seen in almost all research on AI or algorithms versus H-RE, few studies have emphasized the need for more behavioral research to understand consumer behavior motivations.

All those research findings contribute to the AI vs. human comparison literature; however, this dissertation focuses on recommendations under consumer studies and marketing. This focus is covered in the following section.

Table 2.1. Related Studies Investigating AI vs Human Comparison in Consumption Contexts.

Author	Sample	Comparison	Dependent variable	Preference	Findings
(Castelo et al., 2019)	Study 1: N = 250; MTurk, Prolific workers. Study 2: N = 41,592; Facebook	Algorithm vs. human	Having faith in and choosing the advisor	Human (depending on the task)	People trust and rely less on algorithms for tasks that appear subjective (as opposed to objective) since they are perceived as less efficient and more uncomfortable to employ for such jobs.
(Hertz & Wiese, 2019)	Undergraduate students N = 68	AI vs. human	Task type (social vs analytical)	Human	Customers prefer human agents to artificial ones when they have not been informed about the task type. When customers are first aware of the task type, they are likelier to choose a human adviser for social task assignments and an AI adviser for analytical task assignments.
(Z. Li et al., 2020)	Experiment 1: N:40 WeChat students	AI vs. human	Perceived trustworthiness and perceived expertise	Human (depending on the experience)	The recommendation sources influenced users' perceived ease of use.
(Longoni & Cian, 2020)	MTurk workers and museum visitors; nine-study N = 3,647	AI vs. human	Product choice and choice of the recommender	AI (depending on the nature of the product)	When utilitarian (as opposed to hedonic) product characteristics are more significant or salient, people favor AI (as opposed to human) recommenders.
(Wien & Peluso, 2021)	Study 1: N = 177; MTurk, Study 2: N = 195; MTurk, Study 3: N = 245; MTurk	AI vs. human	Consumer reactions	Human (depending on the nature of the product)	A H-RE could be more effective than an AI recommender for hedonic vs utilitarian products
(Srinivasan & Sarial-Abi, 2021)	MTurk workers; Seven-study N = 2,051	Algorithm vs. human	Brand evaluation	AI	Consumers react less negatively to a crisis resulting in brand damage from an algorithmic error rather than a human error.
(Yalcin et al., 2022)	MTurk workers & Prolific workers; Ten-study N = 5,439	Algorithm vs. human	Attitudes toward the company	Human (depending on the experience)	If an algorithm makes the decision, consumers who receive a favorable result have fewer favorable opinions of the business (vs. a human). This discrepancy tempers an adverse decision.
(Xie et al., 2022)	Study 1: N = 112; prolific workers from UK & USA, Study 2 ERP experiment: N = 33; Chinese students	AI vs. human	Purchase behavior	AI	People are more inclined to accept a recommendation provided by AI if they are aware of and sure about their needs.
(S. Li et al., 2023)	Study 1 field study N = 61; So, jump participants, Study 2 Lab exp N= 108; So, jump, Study 3 Lab exp N =120; Credemo participants	AI vs. human	Call Duration	Human	Consumers tend to feel less empathy towards AI tele seller vendors (versus human tele sellers) and, therefore, tend to shut down AI tele sellers faster.
(Ruwe & Mayweg-Paus, 2023)	N = 98 German native speakers	AI Systems vs. peers vs. educator	Feedback on language and effectiveness	AI	Compared to Peer review and Educator review, AI was found to be more trustworthy, especially from the vantage point of its expertise
(Sung et al., 2023)	Qualtrics participants: N: 509	Storytelling agent (ADH vs RH)	Behavioral intentions (brand attitude, brand	Almost equal	When the tale and the product are a good fit, both kinds of agents encourage narrative transportation. Furthermore, positive customer reactions to a digital

			knowledge enhancement, WOM)		human that is viewed as more human-like are stronger, indicating a successful new strategy for storytelling marketing.
Author	Sample	Comparison	Dependent variable	Preference	Findings
(S. Chen et al., 2023)	Credemo, a Chinese data survey platform N:210	Service type (AI chatbot vs human)	Purchase intention	Chatbots	The experience and search products of chatbots and human support are correlated, with chatbots being superior to humans in search product usage.
(Choung et al., 2023)	"MTurk US participants N: 235"	ADM vs. HDM	fairness, competence, trust, and usefulness		Participants considered algorithmic decisions more useful, competent, trustworthy, and equitable than human-made ones. Interestingly, when an applicant was judged unfit for employment, people responded worse to a human decision than an AI decision of the exact nature.
(Jin & Zhang, 2023)	MTurk Workers, Credemo, and WJX.cn; three-study N=790	AI vs. human	Purchase and adoption intention	human (depending on the consumption type)	People believe that human recommendations for experiential products are more knowledgeable than AI recommendations, but AI recommendations for material products are seen as more competent. People's negative perceptions of AI can be lessened by using AI to support human recommendations for experiential products.
(Im and Lee 2023)	Preliminary study 1 N:511 Amazon MTurk, Preliminary Study2 n = 56 University students, Main Study N:194, Amazon MTurk	AI vs. human	Willingness to follow recommendations	Human	Consumers are more likely to follow recommendations made by a human than recommendations made by AI, and the perceived creativity of the recommender explains the effect
(Yang et al. 2024)	N: 240, Profolic participants	AI vs. human	Purchase intention, willingness to pay, attitude, and acceptance intention		People respond more negatively toward the vice (vs. virtue) frame products AI (vs. human) recommended.
(Flaswinkel and Decker 2024)	Prolific US participants N:216, working full-time.	Algorithm-based vs. friend-based	Users' intention to listen to the recommended content	Human	- Users showed a significantly higher intention to listen to friend-based recommendations than algorithmic ones. - Higher levels of PVA weakened the impact of the recommendation source.
(Song et al. 2024)	WJX participants N:287	AI vs Human	Purchase intention	AI (depending on the nature of the product)	- AI endorsers increase purchase intention for search products. - Human celebrity endorsers are more effective for experience products. - Self-image congruency mediates AI's effect; functional congruency mediates human endorser's effect.
(Yueyan Zhang et al. 2025)	Study 1a N: 130, Study 1b N:200, Study 2a & b: N: 400, Study 3: N: 400 participants through the Credemo	AI vs Human	Trust, Empathy, Persuasion	AI (depending on the rational or emotional context)	- Human influencers generally elicit more empathy. - AI influencers can outperform humans in trust/persuasion if strategically positioned (e.g., in functional contexts).
(J. Huang et al. 2025)	34 healthy participants from Liaoning Normal University	Human, Virtual Assistant, Robot	Consumer Decision (Behavioral vs Neutral Evidence)	Human	Gender stereotypes transfer to AI, but effectiveness depends on AI embodiment and task context. Female agents perform better due to associations with service roles, especially in hedonic settings. Robots align more with utilitarian tasks, while virtual assistants better match hedonic recommendations.

2.2.2 AI vs Human Recommenders

As was mentioned previously, the comparison between AI and humans garnered attention under the AI vs. Human comparison almost twenty years ago. Despite the evidence that shows that AI-RS performs superior to H-RE (Grove et al., 2000; Huseynov et al., 2014; Kapania et al., 2022; Longoni & Cian, 2020; Thorey et al., 2019; Wien & Peluso, 2021), there are situations with medical, legal, or psychological consequences where people will have more confidence in humans for getting advice (Dietvorst, Simmons, and Massey 2015; Lindquist and Dautaj 2020; Castelo, Bos, and Lehmann 2019; J. Chen et al. 2021; Saragih and Morrison 2021; Wu et al. 2021; Bawack and Bonhoure 2022). In other words, although AI recommenders outperform humans in those circumstances, research shows that people still prefer H-RE to AI recommenders (Longoni & Cian, 2020; Önkal et al., 2009; Waytz & Norton, 2014; Wien & Peluso, 2021; Yeomans et al., 2019). This avoidance is called algorithm aversion (Dietvorst et al., 2015), and people who hold it believe that algorithms are incapable of handling complex, complicated, human-centric tasks. This triggers algorithm aversion and pushes consumers to seek out H-RE, especially in circumstances where the situation calls for subjective, hedonic, or personally unique tasks (Longoni, Cian, et al., 2022). Even if the algorithm occasionally makes a mistake and provides an incorrect recommendation, this validates people's algorithmic aversion and H-RE preference (Dietvorst et al., 2015). However, this does not necessarily mean that consumers are averse to algorithms in every circumstance. One of the recent studies mentioned earlier stated that consumers present less aversion to algorithms when the recommendation is regarding their search history (Xie et al., 2022). This means that when the consumer knows the product they want to buy after a brief browsing history, consumers may accept the algorithmic recommendation as it will reduce their search effort and positively contribute to their decision-making process. This idea supports the distinction between hedonic and utilitarian consumption concerning the recommenders' type, whether AI or human (Longoni & Cian, 2020), as consumers' search history, might be considered utilitarian consumption.

With all the information that has been stated to summarize the AI vs. H-RE literature so far, the following hypothesis is proposed:

H1: Consumers' response depends on the recommender type. Consumers may respond differently depending on whether they receive a recommendation from a human or an AI recommender.

This dissertation also suggests that some personalized product recommendations can generate an adverse reaction, even though they are products that potential customers are looking for and intend to buy. To investigate the motivations behind this negative attitude, the recommended product's effects on the user's identity and behavior will be explained in the next section.

2.3 Identity Signaling to Reference Groups Through Recommendations

Consumers' decisions to purchase a product are not based solely on its functional (utilitarian) or hedonic attributes. These characteristics often carry symbolic meanings; helping individuals gain social respect, express themselves (Atasoy and Morewedge 2025, 530), and signal belonging to a particular group (i.e., reference groups). In other words, consumer attitudes are shaped not only by their social environment (Grubb and Grathwohl 1967) but also by the influence of reference groups, especially when these groups represent identities consumers wish to either associate with or avoid (K. White and Dahl 2006; K. White and Argo 2007).

In this context, recommendations, particularly personalized ones, are not just neutral recommendations. Whether recommending a product, service, or experience, such recommendations carry social cues and link consumers to specific identity groups. If the association aligns with an undesirable identity group (i.e., a dissociative reference group), it can provoke discomfort or even trigger a social identity threat.

Therefore, it is critical to understand how consumers interpret these recommended products and whether they associate them with desired or undesired reference groups.

In the following section, the symbolic role of products and how consumers perceive them will be explored, and then how personalized recommendations may signal associations with dissociative reference groups, raising identity-related concerns, will be discussed.

2.3.1 The Role of the Recommended Product

As stated before, products are not only functional entities but also symbols that consumers use to express themselves (Belk 1988). Traditional practices, religious beliefs, morals, and socioeconomic classes are elements that help define not only consumption behaviors but also people's personalities. Social identities, and thus how society lives, inevitably affect attitudes towards products and consumption behaviors (Odabasi & Barış, 2012,211, quoted in Kılıç 2021). This symbolic value becomes more salient when products are associated with culturally sensitive annotations or reference groups. For some, especially for men, personal care products are considered private products, while for others, hemorrhoid creams, laxatives, or birth control pills (Dahl et al., 2001; Wrobel, 2002) can be considered as shameful to be known. As a result, perceptions of products, brands, and communities are impacted; what one sees as a life-enhancing product, another might perceive as identity threatening. To give an example of this perception, even though studies have shown that the consumer choice and consumption of women's underwear is part of a woman's feminine identity, self-image, or self-concept (Amy-Chinn et al., 2016; Jantzen et al., 2016; Tsaousi, 2011, 2014; Vigolo & Ugolini, 2016), there is still a widespread belief in some cultures that lingerie is only bought to send subtly suggestive signals to the other sex not to enhance a woman's sense of femininity (Begum and Barn 2019); therefore, they may be seen as private product that their public visibility can elicit embarrassment and fear of judgment. Such associations are often internalized by consumers, particularly women, who must negotiate between personal choice and societal judgment. The literature on *private* or *embarrassing* products reinforces this notion. Dahl et al. (2001) and Wrobel (2002) found that consumers are more likely to avoid situations where others might infer sensitive information based on their purchases. Again, in Kılıç's study, two concerns were clearly expressed by the participants when considering the perception of private products and the concerns about purchasing private products in online shopping: first, the fear of caching browsing history and, therefore, the possibility of retargeting; second, the fear of the customer's social circle hearing about the thing they purchase (Kiliç 2021, 109). So, considering the presumption of “you are what you consume” (Ahmed, 2015; Balıkçıoğlu, 2016), gender stereotypes and stigmata regarding women's clothing preferences, a personalized recommendation that exposes underwear or lingerie preferences may be perceived and interpreted as promiscuity or moral laxity (Begum & Barn, 2019) This can trigger negative emotions in the prospect, such as the social anxiety, embarrassment, fear of negative evaluation, social identity threat, last but not least stereotype threat, depending on the recommender (human vs. AI).

Functional women's underwear, such as shapewear, may also cause the fear of negative evaluation in the context of self-confidence and anti-body positivity. A participant in another qualitative study on the shapewear brand Spanx said she was undecided about whether to find the message *“Improve your rear view”* used in personalized email advertising offensive or relevant (Zanette and Scaraboto 2019, 449-51). This can easily be interpreted to mean that a person interested in this product is accurately targeted. However, the targeted consumer is annoyed by the personalized message specific to this person. So, what could be the cause of these negative emotions, even if they are targeted accurately? It should not be forgotten that, just as each product has a different meaning for each customer, the reason for discomfort will also be different. Therefore, the question of what the reason for the customer’s negative reaction could be, even if the accurate targeting is made, as asked in the previous paragraph, varies according to the product, but more importantly, depending on the symbolic meaning of the product or the group it associates with. In the next section, social identity and how it affects consumer preferences will be covered to answer this question.

This complexity suggests that the meaning of a recommended product is not static; it is constructed through individual experience, cultural values, and perceived group associations. Thus, the consumer’s discomfort with a recommendation may not stem from inaccurate targeting per se but from the symbolic threat posed by the group, the product implicitly associates them with. The following section examines how associative and dissociative reference groups shape consumer behavior through identity-based signaling mechanisms.

2.3.2 Reference Groups and Associative vs. Dissociative Reference Groups in Consumer Decision-Making

Reference groups are central in forming identity and consumption practices (Escalas and Bettman 2005; 2003, p 341). Consumers often look to others for behavioral cues to emulate or distance themselves in other words (Bearden and Etzel 1982; Kemper 1968), people prefer in-groups and avoid out-groups. This is because they think out-groups disparage them and cannot provide positive connotations, which leads them to reduce their relationships (Jackson, Sullivan, Harnish, & Hodge, 1996, quoted in White and Dahl, 2006, 405). A highly particular kind of out-group is the dissociative reference group. Although some out-groups are not genuinely concerned with the individual, a dissociative reference group is an out-group that the individual is driven to stay away from (White et al., 2014; White & Dahl, 2006). These groups can be associative—groups individuals identify with or desire to join—or dissociative—groups individuals wish to distance themselves from (K. White and Dahl 2006; D. E. Abrams and Hogg 1990). The symbolic meanings assigned to products are often filtered through these group associations.

When a product recommendation implies similarity with a dissociative reference group, it can provoke strong resistance, even when the product is appealing or practical. White and Dahl (K. White and Dahl 2006, 408) found that men were less likely to choose a meal from a menu when the meal was associated with a dissociative group (e.g., women or effeminate men via “Ladies Cut” Steak), even though they had no objections to the taste or quality of the meal. Similarly, Berger and Heath (2007) demonstrate that when a product became popular among a dissociative group (e.g., a stigmatized community), consumers quickly distanced themselves from that product, even if it had been desirable before. Similarly, White and Dahl (2007, 319-20) demonstrated this in an experimental context: Canadian consumers avoided a product when it was associated with a dissociative group (e.g., American) despite the product having functional relevance. In digital contexts, this identity signaling becomes especially fraught.

Algorithmic recommendations based on prior behavior, demographic data, or collaborative filtering may inadvertently link users to dissociative groups. For instance, a woman receiving lingerie recommendations may feel that her private preferences are being publicly labeled or misrepresented. This mis categorization can result in a social identity threat (Steele, Spencer, and Aronson 2002) which may hinder the consumer's sense of identity coherence and belonging.

In contrast, associative reference groups can enhance a product's appeal when the recommendation aligns with the consumer's ideal self-image or social expectations. Escalas and Bettman (2005) show that brand-user imagery congruent with a consumer's desired identity can increase purchase intentions and brand attachment. However, even these associations must be contextually appropriate and carefully calibrated; over-personalization may lead to discomfort if perceived as overly intrusive or manipulative.

From this perspective, identity signaling is not merely a passive reflection of group membership but an active construction process, where recommendations—especially in digital contexts—serve as a form of social categorization. If a product is associated with a group the consumer wishes to dissociate from, the recommendation becomes a social threat, even if it is functionally accurate (Steele, Spencer, and Aronson 2002).

In summary, the product's nature and the social group it symbolically aligns with determine whether a personalized recommendation will be appreciated or rejected. This interplay between product meaning and group association lays the foundation for understanding consumer reactions in personalized digital environments, forming the theoretical basis for the experimental studies in this dissertation.

H2: The effect of recommender type (AI vs. Human) on consumer responses depends on signaling content (associative vs. dissociative reference group).

The following section will explore how these dynamics are magnified or mitigated depending on the stereotypes that may threaten social identity.

2.4 The Effects of Stereotypes and Social Identities on Consumer Decision-Making

Understanding how consumers interpret and react to personalized recommendations requires a nuanced exploration of social identity, stereotypes, and cultural context. This is because each person has a variety of identities, including not only their own self-identity but also many societal identities (K. White, Argo, and Sengupta 2012). After all, they affect how people behave at any given time, or in other words, they decide at what moment which identities they adopt. This occurs because, in the context of recommendations, consumer attitudes towards the recommendation may drastically change when this recommendation linked to specific social groups or stereotypical traits. The attitudes of the recommendation directed toward consumers may shift significantly when they are associated with a certain social group or stereotypical characteristics. This chapter explains the basics of social identity theory and its implications in marketing, the concept of stereotype and sociocultural stereotypes specific to Türkiye, as well as the mediating effect of the SIT that stereotypes can trigger; afterward, it discusses how recommendations, especially AI recommendations can unintentionally create threats to social identity.

2.4.1 Sociocultural Stereotypes and Identity Markers in the Turkish Context

In Türkiye's sociocultural landscape—a society shaped by collectivist values and deep-rooted traditions—products often carry symbolic meanings beyond their functional utility (Banerjee 2008). These meanings are anchored in broader social stereotypes related to gender, age, and social status, acting as identity markers that communicate one's social role, conformity, or deviation from societal norms. In other words, in these collectivist societies, individual identity is deeply linked with social roles and expectations(Belk 1988; J. Berger and Heath 2007; Escalas and Bettman 2005; 2003). Consumption behaviors are not merely personal choices but are influenced by societal norms, leading to the internalization of stereotypes. Betül Balıkçıoğlu's work (2016), titled "The Rhetoric of Self-Image Adjustment: Tell Me What You Consume, and I'll Tell You What It Is," powerfully captures this dilemma, highlighting the fear of being labeled by others based on consumption choices.

Similarly, Banerjee points out that even as globalization and digitalization have diversified consumption patterns, sociocultural institutions still play a central role in defining the self (2008). To delve more into the sociocultural framework of Türkiye's identity-related consumption choices, they are typically shaped by dual pressure, modern against traditional beliefs, and Western versus local cultural expectations (Kılıçbay and Binark 2002; Navaro-Yashin 2020; J. White 2011). This results in a wide range of stereotypes being mapped onto products and consumption behaviors.

When evaluating the literature conducted with Turkish respondents by illustrating how sociocultural stereotypes and identity markers function in Türkiye, particularly through the lenses of social stigma, gender roles, age-based expectations, and identity-driven consumption, each article contributes empirical or theoretical insights into how certain products, consumption choices, or appearance features are linked with social identity and stigma in the Turkish context. For example, specific themes repeatedly emerge: male grooming must conform to traditional masculinity codes; discount shopping may trigger social stigma (Yeniçeri and Uzuner 2023); visible lifestyle products like clothing or beverages convey one's class or value orientation (Atılgan and Köken 2022; Aksoy and Köse 2021; Telli and Ünal 2016); and aging-related products are often avoided due to the fear of being associated with life stages viewed negatively (Cerrah and Baran 2020; Sevim 2018). Each of these patterns contributes to a broader narrative in which consumers are aware that their choices are being interpreted through social norms and stereotypes. This shared concern with how consumption communicates identity—even without direct social interaction—makes these studies especially relevant for understanding the implications of identity threat in consumer contexts.

Taken together, the Turkish literature also verifies a core insight: in a society where *who you are* is often inferred from *what you buy*, products can become risky identity signals, especially when they are publicly visible or linked to dissociative groups. These findings provide a cultural foundation for understanding how consumers might experience discomfort or threat when faced with product recommendations, especially in online environments, if those recommendations appear to associate them with a group they seek to avoid. Such moments of tension are not merely about product fit but perceived identity misalignment.

This backdrop provides the foundation for exploring how social identity theory explains these dynamics, particularly in digital environments where algorithms personalize content and product recommendations based on inferred identity cues. The following section will examine how identity threat, reference group associations, and perceived stereotyping can shape consumer responses to personalized recommendations.

2.4.2 Social Identity Theory in Consumer Behavior

The concept of social identity was first proposed by social psychologists Henri Tajfel and John Turner in the 1970s and 1980s (Turner & Reynolds, 2010) to explain intergroup behavior (Tajfel & Turner, 1986). As Tajfel and Turner state in their book, the social identity theory posits that part of an individual's self-concept is derived from their membership in social groups, and people work hard to keep a good impression of the groups they belong to. When a product, brand, or recommendation aligns—or misaligns—with one's ingroup identity, it affects purchasing behavior and perceived identity coherence. For example, prior research demonstrates that individuals often engage in consumption that affirms their social identities, such as reinforcing masculinity, challenging aging stereotypes, or resisting prescribed gender norms (Brough et al. 2016; McNeill and McKay 2016). Conversely, products perceived to represent a dissociative reference group (a group no one wants to identify with) can provoke discomfort, even rejection.

2.4.3 Social Identity and Signaling in Recommendations

Whether made by humans or AI systems, recommendations implicitly carry assumptions about the user. Consumers often interpret these recommendations as indicative of who they are or how they are perceived. When there is a mismatch between a recommendation and the consumer's identity, discomfort can arise, especially when the product aligns with a dissociative group or stereotype.

This discomfort is known as *social identity threat*: the feeling that one is being judged or devalued based on group membership or associated stereotypes (Steele, Spencer, and Aronson 2002; Spencer, Logel, and Davies 2016). For instance, a woman who does not conform to traditional femininity norms might find recommendations for stereotypically feminine products intrusive or alienating. Similarly, a person sensitive about body image may react negatively to being shown plus-size clothing, even if no one else sees the recommendation.

AI-based recommendations are particularly susceptible to triggering such threats due to their impersonal and data-driven nature. Unlike H-RE, AI lacks contextual sensitivity and empathy, making it more likely to offer recommendations perceived as misaligned with users' social identities. Human-generated recommendations, by contrast, may be interpreted as more culturally and socially attuned, thus mitigating identity threats.

Thus, this dissertation explores the varying impacts of AI versus human recommendations on social identity threats, highlighting how perceived stereotyping in algorithmic recommendations can shape consumer response. Before hypothesizing this situation, social identity threats will be briefly reviewed in the next section.

2.4.4 The Mediating Role of Social Identity Threat (SIThr)

When the good perceptions of the groups that individuals belong to are challenged, people feel threatened, which might emerge as unpleasant feelings or reinforce behaviors that conform to social standards (Walton & Cohen, 2007 quoted in Moss 2016), which is called social identity threat (henceforth SIThr). It is argued by some scholars that SIThr is a subcategory of stereotype threat (Moss, 2016).

SIThr is the anxiety that people have when circumstances arise that threaten the favorable image through the activation of dissociative group stereotypes or by the devaluation or stigmatization of the ingroup (Steele et al., 2002). Since every individual has at least one social identity, which is occasionally the object of a negative stereotype, everyone is possibly vulnerable to stereotype threat (Spencer et al., 2016), which refers to circumstances in which people fear being evaluated negatively (Moss, 2016).

To give an example for those situations, it can be a consumption of a demerit good that can lead to the need for protecting social identity (Özhan Dedeoğlu & Başaran, 2022), an invisible consumption or dissociative behaviors that can protect an individual's masculine identity (Brough et al., 2016; Brunæs & Pakzamir, 2021; Byrne & Milestone, 2022; McNeill & McKay, 2016) or protection of self from any kind of stereotype threats such as femininity, sexuality, aging (Amatulli et al., 2018; Craig & Gray, 2020; Westberg et al., 2021; Zanette & Scaraboto, 2019), etc.

In line with the information given, the research hypotheses were developed as follows.

H3. The effect of signaling content on consumer responses is mediated by SIThr.

H4. Recommender type affects consumer responses via a serial mediation pathway through signaling content and SIThr.

Although personalized recommendations made via AI-R are set for potential customers' eyes only, the possibility that anyone will somehow see it or label the consumer in a way they do not associate with it can create a negative reaction in the consumer. This may be due to the idea that AI-based recommendations shaped by consumer behavior will not change easily. It is necessary to enter a vast amount of different and latest information into the AI-based system to change the recommendations.

Given these identity-related vulnerabilities, it becomes essential to understand the nature of the threat's consumers experience and how their broader evaluations of their social groups influence these reactions. The following section introduces the concept of collective self-esteem—a construct reflecting individuals' evaluations of their social group membership—and explores how it moderates consumer sensitivity to identity-threatening cues in recommendation contexts.

2.5 Collective Self-Esteem

The origins of self-esteem as a construct go back to William James (1892) according to Smith and Mackie's definition, *"The self-concept is what we think about the self; self-esteem, is the positive or negative evaluations of the self, as in how we feel about it."* (E. R. Smith & Mackie, 2007, 107). Self-esteem is a fundamental human need in many theories. In his *Hierarchy of Needs*, Maslow outlined two distinct types of esteem: the need for respect from others and the need for self-respect (Maslow, 1981). Those with a prominent level of self-esteem can make decisions based on what they believe to be the best course of action, trusting their judgment and not feeling guilty when others disagree. In contrast, people with low self-esteem depend on what others may think of them (Bonet, 1997). Genetic factors, physical appearance (such as weight, height, figure, etc.), mental health conditions, socioeconomic situations, traumatic emotional events, social stigma, peer pressure, or bullying are only a few of the causes of low self-esteem (Jones, 2003).

In contrast to individual self-esteem, which focuses on the individual's personal evaluation of their self-worth, collective self-esteem centers on how individuals feel about the social groups to which they belong. This construct is grounded in social identity theory, which posits that people derive a significant part of their self-worth from group memberships (H Tajfel and Turner 1986). Therefore, collective self-esteem directly informs how individuals perceive threats to their social identity and how these perceptions influence their behavior, especially when exposed to group-based stimuli such as product recommendations tied to particular social or cultural affiliations.

For this dissertation, which investigates consumer reactions to personalized recommendations that may evoke identity threats related to group membership, collective self-esteem provides a more relevant and nuanced perspective. This is because the central focus of the research is on how individuals' group memberships, rather than their self-worth, impact their reactions to recommendations tied to associative and dissociative reference groups. Collective self-esteem (henceforth CSE) is an important psychological construct that explains how individuals evaluate the worth of their social groups, and it is particularly relevant when studying consumer behavior in contexts where group membership and identity play a significant role. This section explores the relationship between CSE, SIThr, and consumer responses to personalized product recommendations, especially when these recommendations may relate to associative or dissociative reference groups.

2.5.1 Collective Self-Esteem vs Rosenberg's Self-Esteem

In this dissertation, CSE is the central construct to understand consumer behavior in the context of identity threats. CSE refers to evaluating one's social identity based on group membership rather than individual self-worth (Luhtanen and Crocker 1992). This construct is fundamental in consumer behavior as it explains how group affiliations—such as cultural, professional, or social group identities—affect individuals' responses to product recommendations. When consumers are exposed to recommendations from dissociative reference groups (i.e., groups from which they wish to distance themselves), their CSE may be threatened, influencing their purchasing behavior.

In contrast, Rosenberg's self-esteem scale (1979) primarily measures individual self-worth and personal self-esteem, focusing on how people feel about themselves on a personal level. Although Rosenberg's self-esteem is widely used in consumer behavior research, it is less suitable for studies investigating how social identities, shaped by group memberships, affect consumer decisions. Unlike individual self-esteem, CSE is more relevant for exploring how group dynamics, particularly in response to SIThrs, influence consumer attitudes and actions.

CSE, as measured by scales such as the Collective Self-Esteem Scale (CSES), includes dimensions that specifically assess how people feel about the social groups to which they belong (Luhtanen and Crocker 1992). These dimensions include membership esteem (CSE-M)—the perceived value of being a member of a particular group—private collective self-esteem (CSE-Pri)—the individual's private evaluation of their group membership— public collective self-esteem (CSE-Pub)—the individual's perception of how others view their group and importance to identity (CSE-I)—the degree to which group membership is a central part of an individual's self-concept.

Focusing on CSE, this dissertation can more effectively capture how group-based identity is tied to consumer behavior, particularly when product recommendations may trigger feelings of SIThr.

2.5.2 Moderating the Role of Collective Self-Esteem on Social Identity Threat

According to social identity theory, people are driven to develop and preserve positive self-concepts. Thus, some researchers, including Michael Hogg and Dominic Abrams, propose that strong social identity and self-esteem are somewhat related. The "self-esteem hypothesis" predicts two ways in which self-esteem and in-group bias are related. First, effective intergroup discrimination boosts self-esteem. Second, low or threatened self-esteem encourages prejudice against other groups (D. E. Abrams & Hogg, 1990; D. Abrams & Hogg, 1999; Brown, 1999).

Although in this dissertation, it is presumed that the consumer's response is dependent on the recommender type, the consumer's self-concept has an impact on attitudes towards the recommender, firm, brand, or even AI, which can, in extreme cases, lead to AI-phobia (C. Y. Wang et al., 2020).

Therefore, this leads to testing another assumption in this dissertation that high CSE will trigger social self-threat depending on the reference group stimuli.

H5. The effect of recommender type on SIThr is moderated by CSE. This effect is stronger for individuals with high collective self-esteem

2.6 The Moderating Role of Stereotype-Related Fear of Negative Evaluation (SR-FNE)

The present study investigates how algorithmic recommendations that reflect social group-based assumptions may trigger *stereotype-related threats* in consumer contexts. As the psychological construct of primary interest is stereotype threat, this section begins by reviewing its theoretical foundations. However, despite its relevance, it has been noted that existing stereotype threat measures are predominantly tailored to academic or occupational performance settings and are not directly applicable to algorithmic personalization in digital marketing. Therefore, after careful theoretical consideration, it was determined that fear of negative evaluation (henceforth FNE) provides a conceptually aligned and empirically validated alternative for operationalizing stereotype-related threats. FNE captures the affective core of stereotype threat—namely, the anxiety associated with being judged or evaluated negatively by others. By synthesizing insights from both constructs, this study introduces the concept of stereotype-related fear of negative evaluation (henceforth SR-FNE) as a moderating factor that intensifies consumers' responses to identity-threatening recommendations. Accordingly, the following sections outline the theoretical background of stereotype threat, then define SR-FNE and explain how SR-FNE serves as a proxy measure for stereotype-related evaluation concerns in digital consumer environments.

2.6.1 Stereotype Threat

When the good perceptions of the groups that individuals belong to are challenged, people feel threatened, which might emerge as unpleasant feelings or reinforce behaviors that conform to social standards (Walton & Cohen, 2007 quoted in Moss 2016), which is called SIThr. Some scholars argue that SIThr is a subcategory of stereotype threat. Stereotype threats refer to circumstances in which people fear being evaluated negatively (Moss 2016). Since every individual has at least one social identity that is occasionally the object of a negative stereotype, everyone is possibly vulnerable to stereotype threat (Spencer, Logel, and Davies 2016).

Stereotype threat refers to the psychological experience of anxiety or concern in a situation where a person has the potential to confirm a negative stereotype about their social group. This concept was first introduced by Steele and Aronson in 1995 in the context of African American students' academic performance. When individuals are aware of a stereotype about their group, suggesting they will perform poorly, the anxiety that they might confirm this stereotype can impair their performance. These emotional and cognitive responses—such as anxiety, self-doubt, and hyper-awareness—mirror those captured by the FNE scale. Indeed, a core component of stereotype threat is the fear of being judged through the lens of a stereotype, which is conceptually aligned with FNE (Schmader, Johns, and Forbes 2008). This theoretical overlap offers a strong justification for operationalizing stereotype-related concerns through FNE measures.

2.6.2 Fear of Negative Evaluation (FNE)

Fear of Negative Evaluation (FNE) is a state of fear and anxiety experienced by an individual that may lead to perceptions of being judged, criticized, excluded, and negatively evaluated by others. (Çaçan 2020). According to Weeks et al. (2005), the primary and fundamental reason for the social anxiety experienced by the individual is the fear of being evaluated negatively by others. According to Darcy, Davila, and Beck (Darcy, Davila, and Beck 2005), social anxiety is a condition in which individuals experience extreme fear that other people will negatively evaluate them in a social environment and focus their attention on them.

In addition, in Çaçan's study, Dilbaz (1997) also defined social anxiety as an individual's fear that other individuals will evaluate them or that they will fall into an embarrassing situation. In the field of marketing, social anxiety refers to the various social fears that users experience, from social distress to shyness (de Bérail, Guillon, and Bungener 2019). This reflects the psychological state of people, as well as how they behave in a social situation. (Yuan, Zhang, and Wang 2022)

While initially developed within the context of social anxiety, the FNE construct has proven instrumental in understanding various forms of evaluative concerns across domains, most notably in the context of stereotype threat and SIThr. Fear of negative evaluation Scale (the brief fear of negative evaluation scale-BFNE) Leary (1983) improved tolerance to be considered hostile by the individual or others for measuring self-report scale. To achieve the purpose of the research, the "Fear of Negative Evaluation Scale" developed by Leary(1983) and adapted to Turkish culture by Erkan, Çam, and Güçray (2003) consists of 12 items containing expressions of fear and anxiety.

2.6.3 The Role of Stereotype-Related FNE in Consumer Identity Concerns

The stereotype threat and the FNE are closely related notions. The fundamental psychological mechanism that underlies stereotype threat is FNE. When people experience stereotype threat, they frequently worry that they will be assessed or judged according to unfavorable preconceptions about their social group. This fear can affect how consumers respond to recommendations. The expectation of social assessment holds significant importance in algorithmic contexts, wherein individuals might perceive personalized recommendations as indicators of their labeling rather than unbiased recommendations. When such recommendations align with undesired stereotypes, such as gendered, racial, or age-related associations, they can provoke discomfort, defensiveness, and identity-related concerns.

The reliability of the FNE scale has been demonstrated through comprehensive validation across a range of groups and circumstances. The FNE scale has been extensively validated and will be used to evaluate the effects of stereotype threat in this research. In other words, how stereotype-related FNE strengthens identity threat effects. It is especially well-suited for examining the psychological consequences of AI-driven personalization, which, while automated, may feel socially revealing to the consumer.

Consumers with higher levels of FNE are particularly vulnerable to identity threats that stem from perceived stereotyping. For instance, when an AI system suggests weight-loss supplements to a woman or technical products to a man based on inferred gender roles, these recommendations may not only feel impersonal but also identity-threatening. Although these recommendations derive from an algorithmic process, they may be interpreted as retaining socially stigmatizing perspectives, resulting in adverse emotional reactions, a sense of distrust, or avoidance behaviors. These reactions extend beyond simple rational objections; they are deeply embedded in the affective mechanisms that FNE explains.

This dissertation uses the FNE scale to investigate how SR-FNE functions as a moderating variable. Specifically, it proposes that consumers with high levels of SR-FNE are more sensitive to stereotype-driven identity threats, resulting in more negative reactions to the recommendation and potentially to the recommending platform itself. This connects with broader concerns about algorithmic bias and the inadvertent reinforcing of undesirable social groups through digital personalization.

Furthermore, the SR-FNE framework offers both theoretical and practical benefits. Theoretically, it sharpens the awareness of individual discrepancies in customer responses to stereotype threats. Practically, it provides a diagnostic tool for evaluating interventions to mitigate algorithmic harms, such as increasing transparency or offering diverse product representations. In this context, SR-FNE captures the emotional resonance of identity threat and allows for measurement of how effectively platforms can alleviate such tensions.

While stereotype threat is concerned explicitly with confirming negative group stereotypes, SIThr encompasses a broader range of experiences where an individual's sense of self, belonging, or group membership is challenged (Steele, Spencer, and Aronson 2002). Measuring SR-FNE helps capture the psychological amplification when stereotype and identity threats intersect. Given the theoretical overlap and amplification function, SR-FNE is expected to moderate the relationship between SIThr and consumer responses. Thus.

H6. The effect of SIThr on consumer responses is moderated SR-FNE. When SR-FNE is high, the negative impact of SIThr on consumer response becomes stronger.

This psychological vulnerability, however, does not operate in a vacuum. While consumers may feel misrepresented or stereotyped, their ultimate reactions to recommendations are shaped not only by personal sensitivity but also by contextual factors, most notably, the perceived value of the product being offered. As such, the following section explores how perceived price or value can interact with stereotype-related concerns, potentially mitigating or exacerbating consumer responses.

2.7 The Moderated Role of Perceived Price (value)

As stated previously, consumers base their purchasing decisions on their functional benefits and the symbolic meaning associated with those products. When consumers are presented with a recommendation linked to a dissociative group, their instinctive response may be rejection due to social discomfort or misalignment with their identity. This discomfort is often amplified when the personalized recommendation is perceived as being tied to a dissociative stereotype, suggesting that the recommender (H-RE or AI-R) classifies or misevaluates customers (J. Berger and Heath 2007). Therefore, the consumer is expected to have a negative attitude. However, the negative attitude towards the recommendation that poses an identity threat, or more specifically, the tendency to reject the premise, is not immutable. It was assumed that the compelling price would moderate this resistance or reactance. In other words, even in the presence of a stereotype threat or identity threat, the price can potentially reduce or even override the initial negative attitude, especially when the price is reduced and framed as a *special discount.*

This section addresses when and how the perceived price (henceforth PP) reduces the effect of the stereotype threat and SR-FNE

2.7.1 Price as a Justification Mechanism

In previous literature, price has been conceptualized as an economic determinant and a psychological justification mechanism (Kivetz and Simonson 2002) A low price enables consumers to rationalize their behavior economically rather than interpret it as an identity statement. In other words, price has the capacity to shift identity-based consumption into functional consumption as individuals align their behaviors with the homo economicus model when economic factors become salient (Reed et al. 2012). As a result, even though the product does not reflect the customers' style, the state of mind that *"the discount is too good to pass up"* (Holdridge 2024) allows consumers to separate the product choice from their social self-concept. This price-based rationalization weakens the salience of identity concerns, particularly among highly price-sensitive consumers (Kivetz and

Simonson 2002) whose decisions are more strongly influenced by economic utility than identity expression (Grewal, Monroe, and Krishnan 1998). Therefore, consumers can disassociate themselves from the potential social meanings attached to the product. In such cases, price operates as a justification mechanism. A low price enables consumers to rationalize their behavior economically rather than interpret it as an identity statement.

2.7.2 Price-Identity Conflict

While price offers a potential escape route from identity threat, it does not function uniformly across all consumers. The dynamics between price and SIThr are even more complex when factoring in SR-FNE. Consumers high in SR-FNE are acutely concerned with how others perceive them and are particularly reactive to products or recommendations that may evoke stereotype threat (Leary 1983). When a recommendation is associated with a dissociative group, such individuals are likely to experience elevated identity threats, fearing that the product choice communicates an undesirable social affiliation (K. White and Argo 2007; K. White, Argo, and Sengupta 2012) it actively signals the risk of being stereotyped, misjudged, or publicly misrepresented.

In such cases, PP becomes a critical moderator. A low price can provide a convenient rationale for accepting a recommendation despite identity misalignment, reducing the negative emotional and evaluative consequences of SR-FNE. On the other hand, a high price reinforces the symbolic and identity-signaling weight of the product, making the threat more difficult to dismiss. This dynamic creates a classic price–identity conflict, in which consumers must negotiate between economic value and self-concept preservation. The tension is especially salient for individuals sensitive to social evaluation, as they are more likely to interpret identity-threatening cues in recommendations and weigh them heavily in decision-making. Therefore, the following hypothesis is proposed:

H7. PP (value) moderates the impact of stereotype-related SR-FNE on the relationship between SIThr and consumer responses. When the product is perceived as lower in price (higher value), the negative effect of identity threat on consumer response is weakened, especially under high SR-FNE.

3-Way Moderated Mediation (Advanced Interaction):

H8. The conditional indirect effect of recommender type on consumer response through SIThr is jointly moderated by SR-FNE and PP. Specifically, when SR-FNE is high, and the price is low, the indirect negative effect is reduced.

Taken together, all hypotheses highlight the complex dimensions of personalized recommendations, especially at the intersection of SIThr, recommender type, signaling content, and PP, which collectively shape consumer behavior. The following part breaks down the methodology used for testing these propositions, which includes research design, stimulus materials, participant recruitment, and measurement strategies.

METHODOLOGY

3.1 Research Objective

The primary objective of this dissertation is to investigate the possible adverse consumer reactions triggered by behavior-based personalized product recommendations, especially in cases where the recommended products carry dissociative reference group cues. This research also explores whether these effects vary depending on the type of recommender, specifically whether the recommendation originates from an AI-based system or a human sales representative. To test these hypotheses, scenarios, and visuals were developed to simulate realistic shopping environments: In-store billboard mockups were designed for H-RE status, and an e-commerce application interface was created for AI-R status, referencing popular online shopping platforms in Türkiye. In each case, personalized product recommendations were provided, embedded with relevant visual and textual cues to represent associative or dissociative reference groups. In other words, the proposed product is associated with a social group to which the participant wants to belong, an image that evokes an associative reference group, or a neutral image. Texts and images that evoked a dissociative reference group emphasized a social group the participant preferred to avoid. These scenarios were then randomly shared with the participants. The following section contains the details of the experimental design and studies.

3.2 Experimental Design and Study Conditions

Apart from the pre-test applied to evaluate the reliability, validity, and cultural acceptance of the scales translated into Turkish (Sharma 2010; Yasir 2016), as well as the stimulus validity, the experimental design developed in this thesis was prepared based on two online experimental studies, each of which used a mixed factorial structure. 2 (Recommender Type: AI vs. Human) × 2 (Signal Content Reference Group: Relational and Dissociative) crossed with 2 participants in both studies who were randomly assigned to one of four inter-subject conditions—(1) AI-R and associative reference group, (2) AI-

R and dissociative reference group, (3) H-RE and associative reference group, and (4) H-RE and dissociative reference group—2 (PP: High and Low) in intra-subject manipulation. Each participant experienced in-topic manipulation (i.e., high and low price-value) at both levels after being confronted with a shopping experience that included scenarios and visuals that represented these conditions, allowing the study to assess whether perceived value moderated the psychological effects of identity threats. The experimental procedure is the same in both studies, with the only variation being stimuli adapted to gender and age stereotypes. In total, 16 different stimuli have been developed, four different for gender stereotypes and four for age stereotypes, different for men and women, to ensure both contextual and demographic relevance. Randomization was segregated by gender so that participants were exposed only to stimuli related to their gender group in a relational or dissociative design. Study1 focused on age-based identity cues (e.g., young and old) manipulated through imagery and language, while Study2 focused on gender-based identity cues (e.g., gender-neutral presentation of traditionally gendered and gender-appropriate products or models).

Consistent with research highlighting the role of visual cues in stereotype activation and consumer impression formation(Forehand and Deshpandé 2001; Kirmani and Shiv 1998), the study included product images that pointed to associative or dissociative reference group characteristics. All images are sourced from public e-commerce sites (e.g., Amazon, Trendyol) and edited to reflect associative and dissociative reference groups in Canva. All images were free of original marks to avoid brand bias. These manipulations are consistent with existing literature showing that images used to promote the product and wording used to recommend the product may indicate social group associations and influence identity-based processing (J. Berger and Heath 2007; K. White and Dahl 2006). Since the theoretical foundation is based on the idea that individuals differ in their relationships with various social groups, the same product can trigger a variety of psychological responses depending on the individual's perception of the group that that product represents—a recommendation that may evoke a negative emotion for one person may be considered positive or neutral for another person—there are three different general stereotypes (S.E.S., Gender, and Age). These categories were chosen because of their strong relevance to social identity theory (Henri Tajfel et al. 1979) and their welldocumented association with stereotype-driven expectations and dissociative group dynamics in consumer behavior (K. White and Dahl 2007; J. Berger and Heath 2008). As a manipulation check to see if the participant was triggered by cases belonging to these three general stereotypes randomly assigned to them, they were asked whether these personalized recommendations corresponded to the consumer's usual preferences. The details of the two main experimental studies to test the pre-tests and hypotheses applied to evaluate the validity and reliability of the scales translated into Turkish will be given in the next section.

3.2.1 Pretest: S.E.S. Stereotype

Prior to the main studies, preliminary tests were conducted to assess the reliability and validity of the translated and adapted measurement scales, as well as the semantic clarity and stimulus validity of the questionnaire. Therefore, since the questionnaire included 47 statements other than demographic information, stimuli belonging to stereotypes related to S.E.S., gender, and age were randomly shown in a relatively large sample of N=118 (female=81, 68.6%) respondents from different demographic backgrounds via social media platforms. Products for S.E.S. groups are categorized as affordable, luxury, or budget-friendly and are presented with visual cues appropriate to these categories. Within the scope of gender manipulation, lip balm images with masculine or feminine connotations were presented to male participants; Female participants were shown shapewear pictures of plus size and skinny models. In age manipulation, the same pajamas were presented as cotton pajamas in the associative reference group and menopausal pajamas in the dissociative reference group. The results confirmed that visual manipulations effectively activated perceptions of identity cues related to S.E.S. and that there were significant differences in stereotype salience between high and low S.E.S. ($p <.001$), justifying the validity of stimuli for potential use in future studies. To evaluate the basic structure of the scales, exploratory factor analysis was performed on all measurement items included in the study. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.768, and Bartlett's sphericity test was significant (χ^2 = 3257.693, $p < .001$), which confirmed the suitability of the data for factor analysis. The anti-image correlation matrix was examined, and the items with diagonal MSA (Sampling Adequacy Measure) values below the acceptable threshold value of 0.50 were removed one by one. In total, 11 items were excluded across scales, with the most significant reductions occurring on the (CSE) scale. This suggested re-evaluating the Turkish translations, as participant feedback showed that some expressions lacked cultural or linguistic relevance in Turkish. These revisions were expected to increase conceptual clarity and improve construct validity in the main study. With these improvements, the factor structure showed acceptable internal consistency with a KMO of 0.771, above the recommended value for this test. In addition, all scales exceeded reliability thresholds, supporting the validity of the final measurement model. The reliability of these eight constructs, namely FNE, SIT_DC, ATT, CSE-Pub, FNE-R, CSE-Pri, CSE-I, and CSE-M, was found to be 0.931, 0.902, 0.936, 0.804, 0.764, 0.838, 0.781 and 0.783, respectively.

For reliability analysis, Cronbach's alpha of FNE (0,908), PP (0,928), Response (0.936), SIT_DC (0,908), CSE (0,842) exceeded the recommended threshold of 0.70 after item reduction. Also, it is examined that there is a positive correlation between Associative vs Dissociative and SIT_DC ($r = .270$, $p = .003$), Manipulation Check and Response ($r = .708$, $p < .001$), and a negative correlation between Associative vs. dissociative and Response ($r = -.214$, $p = .020$), SIT_DC and Response ($r = -.526$, $p < .001$), Manipulation Check and Associative vs Dissociative ($r = -.365$, $p < .001$). A Three-Way ANOVA was conducted to assess the impact of reference group type (associative vs. dissociative), scenario type (shapewear, menopause, S.E.S.), and their interaction on perceived SIT_DC. The results revealed a significant main effect of reference group type ($F = 8.611$, $p = .004$), with dissociative cues eliciting significantly higher SIT ($M = 3.544$) compared to associative cues ($M = 2.715$). This confirms the theoretical proposition that dissociative signals pose a greater threat to consumers' self-concept. In other words, the dissociative threat effect held consistently across all tested contexts, including shapewear, menopause, and SES-related scenarios. This iterative procedure and preliminary tests confirmed that each construct was psychometrically acceptable for the main experimental design. Despite the relatively substantial mean difference observed in the case of S.E.S., the main studies will continue with age stereotype and gender stereotype scenarios, as S.E.S.-based stereotyping has been extensively studied in the consumer behavior and social identity literature, and there are even new studies published on this subject in Türkiye (Kraus and Stephens 2012; Piff et al. 2010), identity threats due to age and gender stereotypes are still developing research areas in the Turkish academic literature. The following section will provide a comprehensive summary of the main studies.

3.2.2 Study1: Age Stereotype

Study1 investigated how age-based stereotype signaling in personalized product recommendations impacts consumer responses, particularly in terms of perceived SIThr and purchase intention. Age is a core social identity that persists across the lifespan and contributes to the formation of generational in-groups and out-groups. Individuals often view themselves as part of a particular generational cohort (e.g., Millennials) and may distance themselves from older or younger groups based on prevailing stereotypes (North and Fiske 2012) . When product recommendations reflect a dissociative reference group, such as an age group with which the consumer does not identify (Bae and Jo 2024; Amatulli et al. 2018), it may trigger SIThr (Steele 1997; K. White and Dahl 2006), leading to resistance or discomfort toward the recommendation. The biased perceptions of individuals affect signals associated with different age groups. For this reason, in Study1, the entries of Ekşi Sözlük, a digital agora (Ünür and Duman 2024, 197) that ranks first in the user-based dictionary ranking (Gümüş 2023,293) in Türkiye, where social assumptions and stereotypes can be observed (Zeybek 2023), were taken as reference.

For male respondents, as evidenced by the content analysis of user-generated entries in Ekşi Sözlük, the flat cap was chosen as a stimulus due to its dual symbolic connotations in Turkish culture. Some entries associate the flat hat with rural, elderly, or working-class stereotypes, making it suitable for a dissociative reference group symbol, while others link it with an inspirational tone to fictional figures who reflect the urban and masculine style, such as Thomas Shelby. In addition, there were comments on the EkşiSözlük, noting that the flat hat symbolized “father figures of the past” or “outdated masculinity” (see Appendix B). These antonyms are a very accurate example in the Turkish context to test the effectiveness of the flat cap in triggering social identity dynamics based on perceived group membership and visual signaling. In this context, respondents were shown product recommendations that included images of older, rural (dissociation) or younger, stylish, and charismatic (association) models. This allowed us to test whether mismatched age cues would evoke identity threats and alter consumer response.

For the female respondent, based on Vouge Business' article (Webb 2024), it was observed that fashion and beauty culture is youth-centered, and in line with the literature, menopausal women often avoid being explicitly associated with menopause (McCartan 2025; Perianes and Kissling 2020) because they are often presented as older and unattractive women (Vincent, Ménard, and Giroux 2025) . As in the flat cap perception for men, there are many entries about menopause in Ekşi Sözlük. The analysis showed that some entries approach menopause with empathy, understanding, and respect. In contrast, others have been used as insults, especially as a stereotype of a woman who is less sexually active, less desirable and more aggressive see (APPENDIX B). Therefore, built on both the literature and Ekşi Sözlük entries that shed light on the social perspective, the assumption that this stigma can create a dissociative reference group in which individuals' distance themselves from menopause to avoid negative labeling is strengthened. Based on this assumption, the case of female dissociative age-related stereotype was designed in which cotton pajamas were introduced as a product under the "Aging Line" collection for menopausal women, characterized by loose, asexual designs and muted colors that hinted at aging and a retreat from sexualized femininity. This is because such clothing is symbolically associated with bodily decline and invisibility in later life (Clarke and Griffin 2008; Furman 2013) and evokes a form of ageism based on gender (Sontag 1972). Under Associative reference group conditions, the same products were presented to the participants with sportive young models as sweat-proof nightgowns without using the concepts of "aging" and "menopause" (See Appendix H).

To investigate the effect, a 2 (Recommendation Type: Human and AI) × 2 (Signal Content Reference Group: Associative vs. Dissociative) experiment design was applied among the subjects. Participants (N = 220) were randomly assigned to one of four conditions, and each read a scenario simulating a shopping experience in which participants were confronted with carefully selected product recommendations that were either young or neutral (associative) or elderly (dissociative), depending on their gender.

In the associative scenario, female participants were asked to read a scenario and imagine looking for breathable, non-synthetic nightgowns to sleep comfortably at night and in response to hormonal imbalances. Male respondents were asked to imagine checking out stylish, weather-appropriate hats after reviving a renewed interest in hats.

In AI recommender conditions, participants were shown a pop-up notification generated by an algorithm based on prior purchases, search history, and demographic data. Associative AI conditions presented neutral, functional recommendation aligned with the user's current needs and age group. On the other hand, dissociative AI conditions had subtle hints of stereotypes (like “anti-aging comfort wear” and products shown by much older people), which could suggest an unwanted group identity. In all H-RE conditions, participants were approached mid-browsing by a sales representative. The details of the conditions are shown in Table 3.1

All scenarios featured realistic product images and pricing information embedded in the shopping narrative to reinforce manipulation. Participants then answered questions that included measures assessing SIT_DC, CSE, SR-FNE, PP, and attitudes towards recommendation and purchase intention as a key dependent variable.

To explore value-based boundary conditions, each participant encountered a discount-priced and label-priced version of the recommendation in an in-topic design, testing whether price mark out could moderate the relationship between stereotype signaling and consumer response. According to double-action persuasion models (Petty and Cacioppo1986; 2012) price reductions can stimulate intuitive-based decision-making and, in some cases, potentially override concerns about identity mismatch.

This setup allowed us to test whether personalized recommendations reflecting dissociative age stereotypes are more damaging when delivered by humans (vs. AI) and whether a lower price can mitigate the backlash.

Table 3.1. Study 1 – Age Stereotype Experiment Conditions

Condition	Target	Reference Group Type	Stimulus/Message Details
1. Human – Dissociative)	Men	Dissociative	Recommender highlights a classic flat cap model praised for its warmth in cold weather and customer satisfaction, referencing intergenerational purchases (e.g., a customer buying for their father), subtly reinforcing age-based associations and potentially triggering distance from older identity cues
2. Human – Dissociative	Women	Dissociative	Recommender highlights a menopause-specific "Aging" product line with functional claims addressing night sweats and aging symptoms (e.g., hot flashes, skin changes). While medically relevant, this framing explicitly links the recommendation to age and hormonal change, potentially reinforcing gendered aging stereotypes and triggering identity sensitivity around femininity and aging.
3. Human – Associative	Women	Associative	Recommender offers alternative corsets with neutral framing ("These might also interest you") without triggering sensitive age image cues.
4. Human – Associative	Men	Associative	Recommender suggests flat cap options, referencing recent popularity in TV series and celebrity endorsements (e.g., Brad Pitt, David Beckham), potentially reinforcing age-based identity cues and aspirational male stereotypes.

3.2.3 Study2: Gender Stereotypes

Study2 followed the same structural design as Study1, shifting the identity dimension from age to gender. This study investigated how personalized recommendations that evoke gender stereotype violations affect perceived identity threat and consumer resistance. Drawing from consumer identity threat literature (K. White and Argo 2007) the study tested whether product recommendations that imply unwanted gender associations provoke defensive responses, especially when reinforcing stigmatized body norms or femininity/masculinity ideals.

Like race, gender is an essential component of social identity that affects society's norms, expectations, and beauty standards (Eagly and Wood 2012). Gender norms often affect how people look. For example, women are expected to be slim and graceful, while men are expected to be strong and masculine (Heilman 2012) . Because there is always anxiety among men about losing their masculinity, while women's bodies and sexuality are under constant surveillance and oppression (Zeybek 2023). These appearance-based stereotypes become particularly salient in contexts of marketing and product recommendation, where visual imagery is used to suggest personal relevance. As such, Study2 manipulates gender-based visual cues in personalized recommendations—e.g., feminine-presenting male models or plus-size female models—to explore whether incongruent signals from dissociative gender groups provoke psychological discomfort or behavioral disengagement. The rationale here rests on prior findings that individuals actively avoid products or messages that suggest an association with undesired identity groups (K. White and Dahl 2006).

This study also considered gendered self-presentation anxieties, such as concerns over how others might interpret their product usage, based on impression management theory (Goffman 1959) and fear of negative evaluation (Leary 1983). Notably, the study also examined whether AI-generated recommendations might sustain or intensify identity threats, not due to their superiority over human-generated recommendations but because of their persistent nature.

As in the Study1, in Study2, amongst the existing literature, Ekşi Sözlük entries were used to ensure that the selected stimuli are aligned with the Turkish cultural context and product interpretations since, in Türkiye, it is not possible to say that academic research specifically addressing weight prejudice is predominant (Bilgin Ülken and Yüce 2020).

For male participants, lip balm was selected due to the dual symbolic connotations in Turkish culture. Compared to other products, these connotations are more controversial because they have criticized men who use lip moisturizer for going against gender norms. According to some interpretations, this product is specific to women, and it is effeminate men who use it. According to other comments, they evaluated lip moisturizer as a health and personal care need to prevent chapped lips, especially in cold weather conditions. It advocates that the product be considered a gender-neutral care product (see APPENDIX B).

In this context, respondents were shown product recommendations that included feminine-coded images paired with “Korea's most popular brand” and neutral or affirmative masculine product packages, ensuring alignment with the participant's gender identity and avoiding stereotype activation, while for associative cases, male participants were asked to imagine shopping for lip balm after recently taking up outdoor sports. (see Appendix I). For female participants, the product was shapewear (e.g., corsets), which was selected as a dual symbolic product because this product often evokes body-related societal pressures and feminine ideals. These products, while functional, often carry a stigma due to their association with body dissatisfaction and deviation from the thin ideal. Especially when framed as a default recommendation, shapewear can send implicit messages about the consumer's body size, triggering shame and perceived surveillance (Tiggemann and Lynch 2001; Grogan 2021). Female participants were asked to imagine shopping for shapewear (e.g., corsets) for a special event; in H-RE conditions, a salesperson approached the participant mid-browsing and offered product recommendations either neutrally (associative) or with a stereotyped evaluative comment (dissociative)—e.g., "*makes you look two sizes slimmer.*" The details of the conditions are shown in Table 3.2.

In AI recommender conditions, participants were shown on-screen pop-up recommendations presented as algorithm-generated, again reflecting associative or dissociative cues through the product design and tone of recommendation. All participants viewed corresponding product images embedded within the scenario to reinforce the manipulation (See APPENDIX I).

After the scenario exposure, participants completed measures assessing SIT_DC, CSE, SR-FNE, PP, and attitudes towards advice and purchase intention as a key dependent variable. A within-subject price manipulation (low vs. high) was again applied to test whether value considerations could attenuate the negative effects of stereotype-based identity threats.

Table 3.2. Study 2: Gender Stereotype Experiment Conditions

Condition	Target	Reference Group Type	Recommender Type	Stimulus/Message Details
1. Human – Dissociative)	Men	Dissociative	Human (salesperson)	Recommender emphasizes trendy Korean brands of lip balm — the brand imagery/advertising may implicitly be associated with femininity, youth culture, or aesthetic-driven markets that men may want to distance themselves from.
2. Human – Dissociative	Women	Dissociative	Human (Ayşe)	Recommender overtly mentions hiding fat and slimming appearance (e.g., "2 sizes smaller," "hide fat"), which may evoke body image threat or associations with pressure to conform to societal beauty standards.
3. Human – Associative	Women	Associative	Human (Ayşe)	Recommender offers alternative corsets with neutral framing ("These might also interest you") without triggering sensitive body image cues.
4. Human – Associative	Men	Associative	Human (salesperson)	Recommender offers neutral lip balm options, potentially positioned for outdoor activities, with no gendered branding or SIThr implied.

3.3 Sample Characteristics and Data Collection

Based on the assumption that social identities and social norms play a decisive role in individual behavior, this study aims to examine whether some stereotypes specific to Turkish culture cause SIThrs to consumers in Türkiye through personalized recommendations and the effect of this on attitudes. Therefore, the study was conducted with Turkish participants and in Turkish. In this context, the study's primary purpose is not to reach generalizations at the population level but to experimentally examine the effects of personalized recommendations based on behavior. For this reason, it was preferred to include only reachable individuals in the sample; convenience sampling under the non-probability sampling method was chosen by targeting computer and mobile phone users who are likely to represent the online shopping audience. This method was found to be both appropriate in terms of practical application and methodologically consistent with the nature of the study.

Participants consisted of Istanbul Bilgi University graduates, students, staff, and individuals randomly reached through social media platforms (e.g., Instagram, WhatsApp, LinkedIn). Participants were also recruited through Others.com, a platform where university students are paid to collect participants in the survey. Participants sometimes preferred to forward the survey link to others in their networks after completing it. While this extended the study's reach, it was not implemented as a structured or tracked recruitment strategy. Thus, it is best described as an informal referral extension of convenience sampling.

In Study1, stimulus material was related to age stereotypes. Therefore, the study was applied to individuals aged 25 years and older. With regard to GenderSte, which was Study2, it is important to note that gender-related SIThrs can occur throughout the entire adult life (Rudman and Glick, 2008; Steele et al., 2002), no upper age limit has been imposed for sex-dependent sampling.

Approval from the Research and Publication Ethics Board was obtained from Istanbul Bilgi University on October 8, 2024, for the chosen survey questions. After the ethics board's approval, the processes for scale translation, validation, and manipulation designs were finalized, and online surveys were developed using Google Forms. The survey was administered to consumers online from November 14, 2024, to March 20, 2025, encompassing a pre-test phase. A total of 587 individuals who received the survey contributed to the study by filling out the survey. However, 510 of the 587 observations collected could be used in the analysis part of the main studies. Since Google Forms does not provide metadata such as the completion time of the responses, standard deviation and mean control methods were applied to determine whether the participants filled out the survey correctly. Those who gave the same answers, those who filled in the linear expressions with reverse expressions in the same way, those with very low standard deviation (< 0.2), and those who gave extreme answers (6-7 or 1-2) to all questions were removed. Therefore, 11 observations were incomplete, 32 observations were excluded due to a standard deviation of 0, and further observations were removed from the dataset based on their similar responses to linear and reverse questions. This may indicate that participants either lack an adequate comprehension of the scale statements or are completing the survey randomly without paying sufficient attention. In the next section survey structure of the all experiment will be explained.

3.3.1 Survey Structure

As it was states earlier this dissertation used Google Forms' online survey form as a data collection method. The questionnaire consists of three sections. In the first stage, before participants first answered questions about their sociodemographic characteristics (gender, age, relationship status, income status, and education level), they will be asked whether they have ever received a recommendation from a store or an online platform in order to understand their familiarity with the concept. The demographic characteristics were designed with categorical questions of respondents, which will be shown in Table 4.1

The second section includes the scenario the participants are asked to be and the visuals supporting the scenario. The scenarios and visuals were designed to include recommendations made from an e-commerce platform and recommendations offered by a human sales representative. Participants evaluated the suggested products and responded to their perceptions and reactions with the relevant scales. In the survey, participants were randomly assigned to one of four different conditions: (1) AI recommender and associative reference group, (2) AI recommender and dissociative reference group, (3) H-RE and associative reference group, and (4) H-RE and dissociative reference group. Participants encountered a shopping experience that included scenarios and visuals representing these conditions. For example, in an image evoking an associative reference group, the product was associated with a social group that the participant wanted to belong to, while images evoking a dissociative reference group emphasized a social group that the participant preferred to stay away from. Since Google Forms has limited randomization capabilities, a manual redirection script was required to assign participants to random conditions automatically. Specifically, eight separate survey links were created—each corresponding to one of the eight experimental stimuli (four for men and four for women across two studies). For this reason, a Google Sheet was created by running a code via Google Apps Script, which loaded eight surveys created in Google Forms, and a randomly redirected code was run. With each click, the code automatically redirected the participant to one of eight Google Form links. This method enabled robust between-subject randomization while retaining complete control over participant exposure to distinct gender- and age-based stimuli across Study 1 and Study 2.

The third section includes the survey questions. The scales that were used in the survey are going to be explained in the next section.

3.3.2 Scales and Instruments

Apart from demographic variables and three manipulation checks, 44 measurement items were used in this research. The survey form was prepared with two basic structures: categorical questions and likert scale questions. The participants' age, gender, marital status, education level, and most recent monthly income were collected through categorical questions. All other scales were measured using a seven-point Likert scale (Appendix C). The Likert scale, a one-dimensional psychometric tool, is frequently used by researchers to capture participants' attitudes and opinions toward brands, products, or markets, and the items in this study were derived from previously validated scales (Trepte and Masur 2017; Leary 1983). Except for the statements measuring the customer's general attitudes towards personalized recommendations, all scales were evaluated between 1 = strongly disagree and 7 = strongly agree.

SIThr was measured using items developed initially by Homburg and Ukrainets, based on the conceptualization of this construct as a psychological state in which individuals feel at risk of being negatively evaluated due to their social identity (Steele, Spencer, and Aronson 2002) or negative group membership (K. White and Argo 2007). The Turkish adaptation validated by (Yeniçeri and Uzuner 2023) was used in this study and further tailored to fit the context of the recommender type and recommendation scenarios. Specifically, items related to dissociative concerns were adapted from White and Dahl (See Appendix F).

To assess Collective Self-Esteem (CSE), the scale developed by Luhtanen and Crocker (1992) was employed, using the Turkish translation from Arıkan's master's thesis (Arıkan 2017) (See Appendix D). This scale has been widely adapted for various contexts (Keleş 2020; Çoymak 2018; Khare, Mishra, and Parveen 2012; Drążkowski, Trepanowski, and Mikołajczak 2024; Branscombe and Wann 1994; Strauch and Turner-Zwinkels 2019), sometimes adjusted to reflect specific group characteristics, such as gender or race. The scale comprises four subdimensions—membership esteem, individual, collective self-esteem, social self-esteem, and identity importance, with four items per dimension (totaling 16 items).

Translation inconsistencies in the Turkish version were identified and corrected during the pre-test phase. Moreover, to enhance participants' understanding, the abstract term "social group" was replaced with more contextually meaningful categories—specifically, gender and socioeconomic status (S.E.S.) (See Appendix E).

For Stereotype-Related Fear of Negative Evaluation, as explained in Section 2.6, the Brief Fear of Negative Evaluation Scale (Leary 1983) was selected, representing one of three perspectives in the literature on social anxiety. This 12-item scale was used in the version adapted by Çetin et al. (2010), as it better reflects concerns about others' judgments in digital or algorithmic recommendation contexts.

PP (Value) was measured using the scale developed by Dodds, Monroe, and Grewal (1991). The Turkish adaptation by Dağ (2022) was used without modification. This scale allows a more nuanced understanding of participants' perceptions of product value beyond the binary high vs. low price manipulation. While the experimental design includes price manipulation, the PP scale provides This provides richer insights into how individuals' value assessments influence their responses, which is particularly relevant in contexts involving algorithmic or regulated recommendation systems.

To summarize, all constructs in this study were measured using previously validated scales, either directly adopted from existing Turkish versions or adapted from English through a rigorous translation process. A translation–back translation procedure was followed when Turkish translations were unavailable. The original English items were translated into Turkish under the supervision of a marketing academic and subsequently back-translated into English by both a marketing professional and ChatGPT ("Çeviri Geri Çeviri Yöntemi," n.d.)). The back-translated items were compared with the originals, and necessary revisions were made to ensure semantic and contextual equivalence. The final scale wording was determined through expert review and adjusted to align with this research's specific contexts and scenarios.

Consumer response variables—attitude toward the recommendation, perceived personalization fit, and purchase intention—were measured after participants presented a personalized recommendation. Participants responded to two evaluative items: "*What is your general opinion/feeling about this personalized recommendation?*" and *"To what extent do you think you will accept the recommendation?"* These were assessed using three seven-point bipolar items (e.g., 1 = Very Negative/Very Bad/Very Unlikely to 7 = Very Positive/Very Good/Very Likely), adapted from Yalcin et al. (2022, 701) (originally developed byWhan Park et al. (2010)).

Scales that had not been previously translated into Turkish were handled through the exact rigorous translation and back-translation process, with final versions reviewed and refined by an academic expert in marketing. For other scales—including those measuring collective self-esteem (Luhtanen and Crocker 1992) ,fear of negative evaluation (Leary 1983), and perceived value (Dodds, Monroe, and Grewal 1991)—validated Turkish versions(Dağ 2022; Çetin, Doğan, and Sapmaz 2010; Arıkan 2017) were used. However, each was re-examined to ensure its relevance and fit with the current research context and adapted as necessary. (See Appendix D and E)

3.3.3 Conceptual Framework, Model Diagram, and Hypotheses

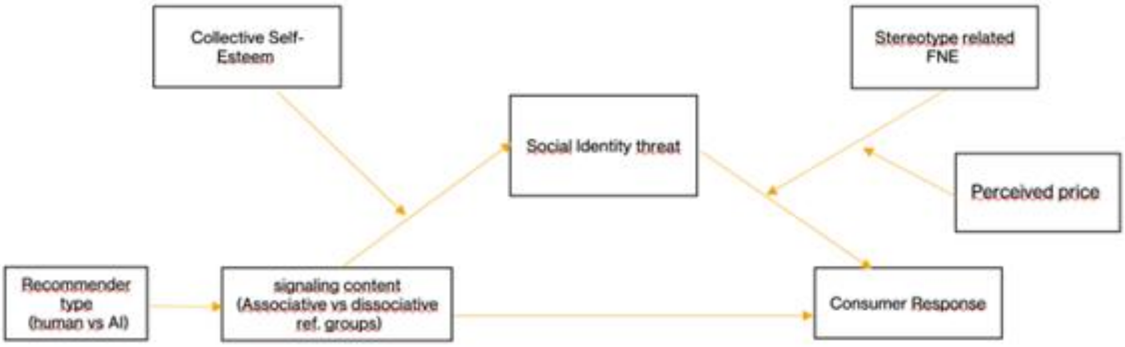
The conceptual framework draws upon social identity theory (H Tajfel and Turner 1986) and personalization inference literature (Sundar and Marathe 2010) to propose that identity-threatening personalization can elicit negative consumer responses, depending on the source of the recommendation and contextual moderators. Specifically, it was posited that the interaction between recommender type (AI vs. Human) and identity-related signaling content (associative vs. dissociative) influences SIThr, affecting consumer responses such as attitude toward the brand and behavioral intentions. This relationship is further moderated by fear of negative evaluation and PP, and self-esteem is proposed to moderate the strength of the effect of recommender type on perceived threat. Table 3.3 presents an overview of the hypotheses and their anticipated signs, which will be examined in the following sections of this research.

Table 3.3. Hypotheses Overview

Main Effects:	Hypotheses	Analysis
	H1. The type of recommender (AI vs. human) influences consumer responses.	T-test
Mediated Effects (Serial Mediation)		
	H2. The effect of recommender type (AI vs. Human) on consumer responses depends on signaling content (associative vs. dissociative reference group).	Two-way Anova
	H3. The effect of signaling content on consumer responses is mediated by SIThr.	Two-way Anova
	H4. Recommender type affects consumer responses via a serial mediation pathway through signaling content and SIThr.	Process Macro - Model 4
Moderated Effects		
	H5. The effect of recommender type on SIThr is moderated by CSE. This effect is stronger for individuals with high CSE.	Process Macro – Model 1
	H6. The effect of SIThr on consumer responses is moderated by SR-FNE. When SR-FNE is high, the negative impact of SIThr on consumer response becomes stronger.	Process Macro Model 14
	H7. PP (value) moderates the impact of SR-FNE on the relationship between SIThr and consumer responses. When the product is perceived as lower in price (higher value), the negative effect of identity threat on consumer response is weakened, especially under high SR-FNE.	Process Macro - Model 18
Three-Way Moderated Mediation (Advanced Interaction):		
	H8. The conditional indirect effect of recommender type on consumer response through SIThr is jointly moderated by SR-FNE and PP. Specifically, when SR-FNE is high, and the price is low, the indirect negative effect is reduced	Process Macro - Model 37

A visual diagram of all the hypotheses seen above is given in Figure 3.1 below.

Figure 3.1. Conceptual Model of the Research



(Source: Developed by author)

3.4 Data Analysis Strategy

The data collected from all studies were analyzed using SPSS and the PROCESS macro for SPSS (A. F. Hayes 2013). The main objective of the analysis was to test the direct, mediating, and moderating effects proposed in the conceptual model, using both between-subjects and within-subjects experimental designs across the studies.

For scale reliability and validity, Cronbach's alpha coefficients were calculated for each construct. Items with low item-total correlations were reviewed and removed where necessary to ensure internal consistency. Descriptive statistics and correlation matrices were examined to assess key variables' basic relationships and check for multicollinearity before conducting regression-based analyses.

To test the hypothesized relationships: The pre-test was conducted to evaluate the reliability and validity of the translated and adapted measurement scales (e.g., dissociative concerns, SIThr, and CSE) before the main data collection phases. This pre-test focused on the Turkish versions of the SR-FNE, SIT_DC, PP, and CSE scales. The primary aim was to ensure semantic clarity, contextual appropriateness, and psychometric soundness of the items within the cultural context of the study. Reliability was assessed through Cronbach's alpha, while validity checks involved exploratory factor analysis (EFA) and expert evaluation. The pre-test results confirmed that the translated scales were internally consistent and conceptually valid, allowing their use in subsequent experimental studies.

Study1 used a 2 (Recommender Type: AI vs. Human) × 2 (Reference Group Type: Associative vs. Dissociative) between-subjects design crossed with a 2 (PP: High vs. Low) within-subjects manipulation to examine the effect of age-based stereotypes in personalized recommendations. Study2, using a similar factorial structure, focused on gender-based stereotypes. The analysis followed the same moderated mediation strategy to assess how recommender type and group association influenced fear of negative evaluation and subsequent consumer responses.

Data was analyzed using SPSS 23.0 and AMOS 23.0. Moderated mediation analysis will be conducted using PROCESS for SPSS, following Hayes (2013). In this model: moderated mediation analyses were conducted using PROCESS Model 1,4,8, 14, and 18, respectively, to test the interaction effects and indirect paths via SIT_DC. To test the interaction effect involving a moderated-mediation model to explore whether low pricing could mitigate the negative effects of dissociative reference group activation using the PROCESS Model 37. Specifically, SIT_DC was modeled as a mediator, with SR-FNE as a moderator and PP as a second-stage moderator. Manipulation checks were conducted after each experiment using one-way ANOVAs and independent samples t-tests. Additionally, covariates such as age, gender, and prior online shopping experience were controlled in regression models where applicable.

Finally, simple slopes analysis and bootstrapping procedures (5,000 samples) were used to probe significant interactions and indirect effects. All analyses adhered to a 95% confidence interval with significance set at $p < .05$. In the H-RE condition, participants were told that a store representative made the recommendation based on the customer's observed preferences. A generic name indicating the gender of the recommender was also provided to avoid ambiguity. In the AI recommender condition, the same recommendation was attributed to an AI system and labeled *Based on your preferences*. Participants were explicitly informed that an algorithm generated this recommendation. After exposure to the recommendation, participants completed the rest of the survey, including manipulation checks for recommender type, stereotype threat, and content effect. Next section is finding section for this experimental studies.

HYPOTHESES RESULTS AND RESEARCH FINDINGS

4.1 Descriptive Statistics for Demographic Variables

Descriptive statistics was used to evaluate the data from the first section of the survey. The tables include frequency information on the age, gender, and educational levels of the respondents. A total of 569 participants completed the study. In order to ensure the validity and reliability of the data, several data quality checks were applied, and participants with questionable response patterns were excluded such as straight-lining (n=38), unusual average response (n=8), and inconsistent patterns on reverse coding (n=13). After applying these data-cleaning criteria, approximately 60 observations were excluded. The final sample size used in analyses was 510. Of these 510 participants, 44.1% (n = 225) were male and 55.9% (n = 285) were female.

Regarding age categorization, the initial descriptive analysis revealed that participants' ages ranged across six categories and the number of participants aged 65 and over (n = 19) was significantly lower than in other age groups, raising concerns about statistical power and reliability in group comparisons. Consistent with best practices in survey research (Tabachnick and Fidell 2018; Hair, Black, and Babin 2010), weak categories that fall below the minimum sample threshold (usually recommended as n > 30 per cell for ANOVA comparisons) can compromise the validity of subgroup analyses. To address this and to provide sufficient statistical power in age-based comparisons, participants aged 55-64 and 65+ were combined into a single category labeled "55+". This unification decision is in line with previous studies, which have had older age groups similarly consolidated for analytical clarity and robustness (Charness and Boot 2009; Moschis 2012). New distribution in both studies ranged across five age categories; 8.0% (n = 41) were between 18-24 years, 23.9% (n = 122) were between 25-34 years, 29.8% (n = 152) were between 35-44 years, 18.8% (n = 96) were between 45-54 years, and 19.4% (n = 99) were 55 years or older.

In terms of experimental condition after the quality check Study1–Age Stereotype distributed as 43.1% (n = 220) and Study2–Gender Stereotype as 56.9% (n = 290). For each study participants were randomly assigned to two different reference group conditions–Dissociative 52.7% (n = 269) vs associative reference group 47.3% (n = 241)– with two different recommender type conditions–AI-R with 48.8% (n = 249) and H-RE with 51.2% (n = 261). Table 4.1 has shown the details of the distribution.

Beyond age and gender, several other variables helped contextualize the findings. The education levels of the sample ranged from high school and below to a doctoral degree. The vast majority of the sample has a bachelor's degree (276%, 54.1%) and 115 people have a doctorate degree (22.5%). This wide range of training allows for further subgroup comparisons and, if necessary, allows training to be included as a control variable in subsequent models.

Regarding relationship status, almost half of the respondents (N = 258) were married. It is followed by the singles with 144 participants (28.2%). Relationship status can influence perceived social identity prominence and interpersonal image concerns, especially in studies involving identity threat and social evaluation. (Leary, 2007).

Since all the demographic variables gathered from the survey are categorical or ordinal, not interval, the distance between categories is not measurable in a meaningful numeric sense. Therefore, for all demographic variables (gender, age, income, relationship status), scatterplots, histograms, or Q-Q plots with normal curves are not applicable or interpretable. Also, it cannot detect statistical outliers because there is no continuous distribution.

4.1.1 Gender, Age and Generation Effect on Experimental Studies

Considering that the two experimental studies were based on age and gender stereotypes, the effects of age and gender were examined in depth in the descriptive analysis. Because the representation of different generations and gender groups allows us to reveal possible differences in responses to personalized recommendations according to the type of recommender and the type of reference group. Of the 510 questionnaires collected on a study basis, 220 (129 women) were related to age stereotypes (Study1) and 290 (156 women) were related to gender stereotypes (Study2). In study1 (AgeSte), the 18-24 age group was intentionally excluded due to the design is tailored for older participants. As a result, age representation is relatively balanced between 25-34, 35-44, 45-54, and 55+, especially for women. In Study 2 (GenderSte), participants from all five age groups were included, providing a broader generational comparison. The largest groups are 35-44 (N = 92), followed by 25-34 and 45-54.

Table 4.1. Demographic Characteristics of Respondents

Variable	Frequency	Sample %
Gender *(Mean=1,56 Std. Dev. =,497)*		
Female	285	55,9
Male	225	44,1
Education Level *(Mean=2,88 Std. Dev. =1,326)*		
High school and below,	30	5,9
Technical secondary school or Junior college	277	54,1
Undergraduate	43	8,4
Master's degree	45	9,0
Doctorate	115	22,5
Relationship status *(Mean=3,23 Std. Dev. =1,507)*		
Single	144	28,2
In a relationship	8	1,6
Engaged,	26	5,1
Married	258	50,6
Divorced	65	12,7
Other	9	1,8
Age) *(Mean=3,17Std. Dev.=1,222*		
18-24	41	8
25-34	122	23,9
35-44	152	30,4
45-54	96	18,2
55 and above	99	19,4
Income *(Mean= 4,46 Std. Dev.=2,229*		
0 - 17.002 TL	83	16,3
17.003 - 30.000 TL	66	12,7
30.001 - 60.000 TL	31	6,1
60.001 - 100.000 TL	46	9,2
100.001 - 150.000 TL	37	7,3
150.001 - 210.000 TL	132	25,9
210.001 TL and above	115	22,5

This cross-generational representation allows us to examine intergenerational differences in responses to personalized recommendations by recommender type and reference group type.

Table 4.2. Characteristics of Studies

Study	Recommender Type		Frequency	Percent %
1 AgeSte	1 AI	1 Associative	43	41,3
		2 Dissociative	61	58,7
		Total	104	100
	2 Human	1 Associative	45	38,8
		2 Dissociative	71	61,2
		Total	116	100
2 GenderSte	1 AI	1 Associative	75	51,7
		2 Dissociative	70	48,3
		Total	145	100
	2 Human	1 Associative	78	53,8
		2 Dissociative	67	46,2
		Total	145	100

As it is stated in the table 4.2 in details, the overall distribution balance for AI vs. Human and Associative vs Dissociative are very close to 50%, indicating successful randomization with slight female majority (56%),

When preferences were analyzed by age and recommender type (AI vs. Human), interesting generational and gender-based patterns emerged. Younger respondents (18-24 and 25-34) showed a distinct preference for either AI or H-RE. On the other hand, in Study2, women between the ages of 18 and 24 had a slight preference for AI (56.7%), while men between the ages of 25 and 34 preferred humans (69.6%). Middle-aged respondents (35-44) exhibited relatively balanced preferences. Older participants (45-54 and 55+) showed more gender-based differences. In Study1, older women (55+) preferred AI (60%), while older men preferred human (56.7%). Conversely in Study2, men aged 45–54 strongly favored AI (71.4%), while women aged 55+ leaned towards human (58.3%). These findings suggest potential generational and gendered differences in trust toward AI systems and perceived appropriateness of algorithmic versus human advice when personalized recommendations intersect with identity-relevant domains.

Income data is also complete across subgroups. Given the potential moderating role of price sensitivity, particularly in investigationg price as a moderator, income should be considered as a control variable in further analyses. As expected ,younger participants (18–24) overwhelmingly fell into low-income categories, consistent with early career or student life stages. income levels increased with age for both genders; however, men were overrepresented in higher income range starting from the 35–44 age group. In Study2, 35+ males showed a sharp rise in high-income distribution compared to their female counterparts.Among those aged 55 and older, both genders showed a strong presence in income ranges above 150.001 TL, indicating post-peak earning patterns. The role of income is particularly important for studies exploring the moderating effect of price sensitivity. Preliminary insights suggest that low-income participants may be more receptive to AI recommenders, especially when paired with value-oriented product appeals. This reinforces the need to include income as a control variable in moderation and conditional process models involving price and recommender type.

The demographic overview presented here demonstrates that the sample provides adequate variation across age, gender, education, relationship status, and income to support robust hypothesis testing. The following section presents manipulation checks to verify the internal validity of the experimental design.

Table 4.3. Summary Table: Demographic Coverage and Representativeness

Variable	Distribution Notes	Analytical Relevance
Age	Full coverage; Study 1 skewed older; Study 2 includes all ranges	Critical for generation-based comparisons
Gender	Balanced representation in both studies	Enables gendered analyses of identity threats
Recommender Type	Fair distribution of AI vs. Human across age and gender	Allows clean testing of H8/H9 moderated effects
Education	Fully observed; no missing data	Potential moderator or control
Relationship	Fully observed; may influence identity salience	Possibly linked to SR-FNE or self-image
Income	Fully observed; key for price-related analyses	Relevant for understanding responses moderated by value sensitivity or price perceptions

4.2 Factor and Reliability Analysis

Exploratory Factor analysis (EFA) was conducted to evaluate the factorability of all items within the model. The Kaiser-Meyer-Olkin (KMO) and Bartlett tests were subsequently conducted to validate that the data set is useful and suitable for factor analysis.

The factorability of selected items was assessed, yielding a Kaiser-Meyer-Olkin measure of sampling adequacy of 0.840, exceeding the recommended threshold for this analysis. Additionally, Bartlett's test of sphericity yielded a significant result ($\chi 2$= 14705,078, p = 0.000). The literature indicates that the anti-image correlation diagonals should surpass 0.5, and our data show that the values of the variables exceeded this threshold.

Subsequent to these measurements, component analysis and varimax rotation were conducted. Analysis revealed eight dimensions, as presented in Table 4.4, with a total variance explained of 70.02% across the nine items. The reliability coefficients for the nine constructs—FNE_L, SIT_DC, PP, CSE-Pri, C_Res, CSE-Mem, FNE_R, and CSE-Pub —were determined to be 0.915, 0.929, 0.953, 0.874, 0.889, 0.726, 0.774, and 0.752, respectively.

It is concluded that there is adequate internal consistency among the items. In the reliability analysis, two factors exhibited values exceeding Cronbach's alpha, though the differences were insignificant; thus, Cronbach's alpha was computed without utilizing the item-deleted values. The hypothesis that the correlation matrix is equal to the identity matrix is rejected, as the p-value is less than 0.5.

4.3 Descriptive Statistics for Key Constructs and Scales

The reliability of all key measures used in this study was found to be acceptable ($\alpha > .70$), indicating satisfactory internal consistency (Nunnally and Bernstein 1994). The variables showed sufficient variance across the sample, supporting their suitability for further inferential analyses.

Table 4.4. Factor Analysis

FACTOR NAME	ITEMS	FACTOR LOADING	VARIANCE EXPLAINED (%)	CRONBACH'S ALPHA
FNE-L	ODK8	0,855	17,152	0,915
	ODK5	0,851		
	ODK6	0,822		
	ODK3	0,816		
	ODK9	0,791		
	ODK12	0,734		
	ODK11	0,733		
	ODK1	0,628		
SIT_DC	SKT2	0,898	15,698	0,929
	SKT1	0,874		
	SKT3	0,865		
	DC3	0,809		
	DC2	0,766		
	DC1	0,715		
PP	PP4	0,933	13,999	0,953
	PP5	0,928		
	PP2	0,919		
	PP3	0,893		
	PP1	0,829		
CSE-Pri	KBS14	0,788	7,8	0,874
	KBS6	0,772		
	KBS16	0,771		
	KBS8	0,745		
	KBS3	0,711		
	KBS1	0,66		
	KBS9	0,612		
C_RES	RF1	0,835	5,801	0,889
	RF3	0,834		
	RF2	0,811		
	raR	0,679		
	ra2R	0,653		
CSE-Mem	KBS4	0,829	3,688	0,726
	KBS2	0,744		
	KBS5	0,67		
FNE-R	ODK7	0,755	2,994	0,774
	ODK10	0,751		
	ODK2	0,686		
CSE-pub	KBS10	0,837	2,895	0,752
	KBS12	0,775		
	KBS7	0,547		
		TOTAL	70,029	
		KMO		0,87
		Bartlett's Test of Sphericity	*Chi-square*	14705,078
			df	780
			p-value	0

Table 4.5 presents the descriptive statistics for the key constructs measured in the study, including Collective Self-Esteem (CSE_T), Stereotype-Related Fear of Negative Evaluation (SR-FNE_T), Consumer Response (C_Res), Perceived Price (PP), and social identity threat & Dissociative Concerns (SIT_DC). All variables were based on continuous scales and analyzed across 510 valid responses.

The mean scores indicate that participants, on average, reported moderately high levels of CSE ($M = 3.79$, $SD = 0.76$) and C_Res ($M = 4.39$, $SD = 1.33$), while their reported SIT_DC ($M = 3.10$, $SD = 1.43$) and SR-FNE_T ($M = 3.18$, $SD = 0.91$) were closer to the midpoints of the respective scales. PP ($M = 3.87$, $SD = 1.67$) also clustered around the midpoint, suggesting that price levels were perceived as neither particularly low nor particularly high overall.

From a distributional standpoint, skewness and kurtosis values were examined to assess normality. According to conventional guidelines (e.g., values between -1 and +1 for skewness, and between -2 and +2 for kurtosis are considered acceptable for normal distribution assumptions; (George and Mallery 2010), most variables demonstrated approximately normal distributions. CSE_T showed a moderately negative skew (Skew = -0.993) with a leptokurtic distribution (Kurtosis = 1.603), indicating slightly more concentration of responses at the higher end. SR-FNE_T and C_Res distributions were close to symmetric and mesokurtic, supporting normality. PP and SIT_DC showed mild positive skewness, particularly SIT_DC (Skew = 0.496), suggesting a slight tendency of respondents to report lower identity threat. Both had negative kurtosis, implying a somewhat flatter distribution.

Table 4.5. Descriptive Statistics of the Variables

Construct	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
CSE_T	510	1.23	5.92	3.7940	0.75863	-0.993	1.603
SR-FNE_T	510	1.09	5.73	3.1758	0.91164	0.328	-0.093
C_Res	510	1.00	7.00	4.3867	1.33208	-0.395	-0.351
PP	510	1.00	7.00	3.8678	1.66895	0.048	-0.855
SIT_DC	510	1.00	7.00	3.1016	1.43085	0.496	-0.601

Overall, the normality diagnostics support the use of parametric statistical tests (e.g., regression, ANOVA) for most variables. However, the positive skew and flatter distribution of SIT_DC should be noted, as this variable may slightly deviate from the assumptions of normality. Where appropriate, robustness checks or non-parametric alternatives can be considered in supplemental analyses.

4.4 Independent Sample and T-Test Results

When examining age and gender differences in responses to recommendation source, a significant effect was observed among female participants aged 45–54. In this group, participants responded more positively to human-generated recommendations compared to AI ($t(28) = -3.63$, $p = .001$). This suggests that middle-aged women may perceive AI recommendations as less trustworthy or more identity-threatening.

No significant differences were found in other gender and age subgroups, although some near-significant trends were noted (e.g., males aged 45–54, $p = .115$). These findings highlight the moderating role of demographic factors, particularly age, on the perceived credibility and influence of recommender types.

According to the results of the independent sample t-test, the responses of female participants aged 45-54 to artificial intelligence (AI) recommendations were found to be significantly lower compared to human-generated recommendations ($t(28) = -3.63$, $p = .001$). This finding suggests that especially women in the middle age group perceive AI recommendations as more of a SIT_DC or find human-generated recommendations more trustworthy. No statistically significant differences were observed in terms of recommendation type in other age and gender groups. These results indicate that AI recommendation systems may be perceived differently according to demographic factors.

4.5 Manipulation Checks

Manipulation checks were conducted to evaluate whether participants accurately perceived the source of the recommendation. To ensure the validity of the experimental manipulation, a manipulation check was performed using the participant's responses to the item *"These recommendations present an image that I prefer, and that is compatible with my style."* The assumption underlying the experimental design was that participants would perceive the recommendation as dissociative if the visual reflected a dissociative reference group. They rated the item three or below (on a 7-point Likert scale) or as associative if the visual reflected an associative reference group, and they rated the item four or above. The results obtained in the pretest (N=118) revealed that the manipulation was quite strong and perceptible. The mean score of the associative group (M = 4.717) was found to be significantly higher than the score of the dissociative group (M = 3.414): t (116) = 4.219, p < .001, Cohen's d ≈ 0.78. These findings confirm the effectiveness of the recommendation source manipulation.

The main study obtained a significant difference in a similar direction (Associative M = 4.448; Dissociative M = 3.201; p < .001). However, the effect size decreased slightly to 0.69 ≈ Cohen's d this time. The manipulation is still meaningful and successful but is not perceived as strongly as in the pretest. One of the possible reasons for this difference is the differentiation of participant profiles in the pretest and the main study. Most pretest participants are in the 25–44 age frame (69%+), which may make them more receptive to recommendation systems and reference groups on digital platforms. In the main study, the sample covers wider age groups, and the proportion of participants over 55 (19.4%) is especially noteworthy. This group is thought to be less sensitive to social identity signals and AI-powered recommendations. Age-group-based manipulation control analyses revealed the details of this differentiation. Comparing the responses to associative and dissociative manipulations in each age group, the results in Table 4.6 were obtained:

These findings show that manipulation works particularly strongly in the 25–44 age group, but these findings show that manipulation works particularly strongly in the 25–44 age group but does not make a difference in the 18–24 age group, and its effect is significant but weak in the group over 55 years of age. This suggests that the way recommender systems are perceived may be age-sensitive and that the influence of social identity signals may vary depending on demographic factors. In addition, a significant interaction was observed between the manipulation content (for example, whether it was an age or a gender stereotype) and the age group. For example: While the 25–34 age group (MD = 1.87, $p < .001$) and the 35–44 age group (MD = 1.55, $p < .001$) had a significant effect on age stereotype manipulation, the manipulation was ineffective in the 55 and older age group (MD = 0.10, p = .849). On the other hand, a powerful effect was observed in Gender Stereotype manipulation, especially in the 35–44 age group (MD = 2.34, $p < .001$), while the manipulation was ineffective in the 18–24 age group (p = .899).

Table 4.6. Manipulation Check Summary Table

Study (Manipulation Check)	Age	Mean Diff.	p	
Age Stereotype	25–34	1.87	.000	Significant and strong
	35–44	1.55	.000	Strong effect
	45–54	1.01	.033	Significant but weaker
	55+	0.10	.849	Not Significant
Gender Stereotype	18–24	-0.09	.899	Not worked
	25–34	1.67	.000	Strong effect
	35–44	2.34	.000	Strongest effect observed
	45–54	1.31	.009	Significant and strong
	55+	1.51	.002	Significant and strong

In addition, respondents' purchase intentions in response to price reductions differed according to the reference group represented by the recommended product. Those in the H-RE status reported being significantly more willing to buy when prices fell ($t(504.72) = 7.169$, $p < .001$; mean difference = 1.10). This suggests that the referrer group represented by the recommended product may influence not only the perceived identity threat, but also price sensitivity and purchasing behavior.

These findings demonstrate the importance of including manipulation checks in experimental designs, particularly in studies involving identity cues or subjective associations, and suggest the need for a more nuanced, conditional analysis to accurately capture the underlying psychological mechanisms.

Performing correlation and regression analyses before proceeding with hypothesis testing provides a strong foundation both methodologically and theoretically. For this reason, regression and correlation analyses will be included in the next section.

4.6 Regression and Correlation Analysis

In this dissertation, three primary statistical strategies were employed to test the hypotheses: factorial ANOVA, regression-based PROCESS macro models, and Pearson correlation analysis. Each of these methods requires, or at least benefits from, a reasonable degree of normality in the data distribution, particularly for dependent variables (DVs).

First, although factorial ANOVA is generally considered robust to violations of normality in large samples, the assumption that the dependent variable is approximately normally distributed remains important, especially in multi-factorial designs such as the present one (e.g., Gender × Recommender × Reference Group). Skewed or kurtotic distributions may compromise the accuracy of the F-test, particularly when cell sizes are unequal.

Second, regression-based analyses conducted through Hayes' PROCESS macro are moderately robust to deviations from normality. However, key assumptions—such as normally distributed residuals, linearity, homoscedasticity, and absence of multicollinearity—are necessary for valid inference in parametric estimation. While normality is not directly required for the independent and dependent variables themselves, it is important for the residuals of the model, and distributional characteristics of the variables can still affect statistical power and interpretation.

Third, Pearson correlation analysis requires both variables to be normally distributed. When normality is violated, non-parametric alternatives such as Spearman's rho are recommended. Since this study also conducted preliminary correlation tests (e.g., between dependent variables and potential covariates such as age or CSE), checking the distribution of these variables was a necessary preliminary step.

In conclusion, the analytic strategy adopted in this research necessitates a thorough normality check—especially for dependent variables—to ensure the appropriateness of parametric analyses and the reliability of the findings.

4.6.1 Correlation Analysis Between Variables

Before proceeding with the regression analysis, Pearson correlation coefficients were examined to evaluate the relationships between the variables and possible multiple connection problems. Analysis of data obtained from 510 participants revealed significant relationships among key variables such as consumer response (C_Res), social identity threat & dissociative concerns (SIT_DC), stereotype related fear of negative evaluation (SR-FNE_T), collective self-esteem (CSE_T), and perceived price (PP).

One of the most striking findings is a moderate and statistically significant positive correlation between consumer response and PP ($r = .245$, $p < .001$). This suggests that as consumers perceive a product to be more expensive, their response—possibly reflecting greater perceived value or quality—also increases. Interestingly, collective self-esteem is negatively related to consumer response ($r = –.150$, $p = .001$), meaning individuals with higher collective self-esteem tend to show lower consumer response, perhaps due to a stronger internal standard or less susceptibility to external influence and positively related to PP ($r = .221$, $p < .001$), suggesting that those with higher self-regard may also interpret higher prices as more justified or appropriate.

The analysis revealed a strong and statistically significant negative correlation between SIT_DC and consumer response ($r = –.609$, $p < .001$). This relationship indicates that SIT_DC is an important negative predictor in the model. A significant and positive relationship was found between SIT_DC and CSE_T ($r = .214$, $p < .001$), indicating that individuals with higher self-esteem are more likely to perceive social identity threats. However, the correlation between SIT_DC and SR-FNE_T was weak and not statistically significant ($r = .073$, $p = .099$). Finally, the strong correlation between collective self-esteem and fear of negative evaluation ($r = .340$, $p < .001$) suggests that individuals who identify strongly with their social groups may also be more sensitive to negative evaluation from others. This relationship may reflect the intertwined nature of social identity and interpersonal evaluative concerns in stereotype-relevant contexts (See table 4.7).

Table 4.7. Correlations Analysis Between Variables

Correlations						
		Response	PP	SR-FNE	SIT_DC	CSE_T
Response	Pearson Correlation	1	,245**	-,006	-,609**	,150**
	Sig. (2-tailed)		,000	,886	,000	,001
	N	510	510	510	510	510
PP	Pearson Correlation	,245**	1	,138**	-,033	,221**
	Sig. (2-tailed)	,000		,002	,450	,000
	N	510	510	510	510	510
SR-FNE_T	Pearson Correlation	-,006	,138**	1	,073	,340**
	Sig. (2-tailed)	,886	,002		,099	,000
	N	510	510	510	510	510
SIT_DC	Pearson Correlation	-,609**	-,033	,073	1	,214**
	Sig. (2-tailed)	,000	,450	,099		,000
	N	510	510	510	510	510
CSE_T	Pearson Correlation	,150**	,221**	,340**	,214**	1
	Sig. (2-tailed)	,001	,000	,000	,000	
	N	510	510	510	510	510

In the age stereotype manipulation condition (Study1), female participants (M = 4.55, SD = 1.34) showed more positive consumer responses than male participants (M = 4.32, SD = 1.36). At the same time, women reported lower levels of perceived threat (Women: M = 2.88; Men: M = 3.06). Regarding PP, men rated the products as more expensive (Men: M = 3.93.

In Study2, which explored the impact of gender stereotype cues in combination with recommender type (AI vs Human), clear patterns emerged across psychological and consumer-related measures. Participants who were exposed to H-RE reported higher levels of SIT_DC (M = 3.31, SD = 1.44) than those exposed to AI-R (M = 3.13, SD = 1.36). This supports the idea that human agents may intensify social identity cues, possibly due to increased anthropomorphism or perceived judgment. Similarly, SR-FNE_T was higher in the human condition (M = 3.37) than in the AI condition (M = 3.20), suggesting greater social sensitivity when humans are perceived as the source of recommendation. CSE_T also followed this trend, being higher in the H-RE group (M = 3.95) than in the AI-R group (M = 3.83). This may reflect participants' increased salience of their social identity under human interaction. In contrast, consumer response (C_Res) was higher for H-RE (M = 4.44) compared to AI-R (M = 4.23), even though identity threat was also higher. This indicates that while threat increases, trust or perceived authenticity in human-generated recommendations might still enhance behavioral engagement. When it comes to PP, again, the H-RE condition led to higher scores (M = 4.19) than the AI condition (M = 3.78), implying a higher perceived value or premium association with human-provided recommendations (Women: M = 3.56). No significant difference in SR-FNE_T levels was found between genders (Women: M = 3.09; Men: M = 2.95).

The effectiveness of manipulation is evident from the systematic differences observed in threat and consumer response variables. For example, although consumer responses were slightly higher for human-generated recommendations (M = 4.44, SD = 1.33) than for AI-generated recommendations (M = 4.33, SD = 1.34), this difference was not statistically significant (t (508) = –0.94, p = .350). This suggests that while the recommender type may slightly influence consumer evaluations, it does not have a strong or consistent effect on consumer response when considered independently from other variables like stereotype threat or identity factors.

In the AI condition, SIT_DC was strongly negatively correlated with C_Res (r = –.629, p < .001) and positively with CSE (r = .278, p = .001).

In the human condition, this pattern persisted SIT_DC ↔ C_Res: r = –.602, p < .001), and SR-FNE_T and SIT_DC were also significantly related (r = .180, p = .030), showing increased interpersonal threat awareness. In both conditions, CSE_T and SR-FNE_T were moderately positively correlated (AI: r = .381, Human: r = .221), indicating that those with stronger group identity were also more evaluation-sensitive (See Table 4.9).

These findings suggest that social categories such as gender and age play a critical role in shaping consumer decision-making processes and interact meaningfully with the recommender type (AI vs. Human). Variables like SIThr, SR-FNE_T, and CSE not only mediate consumer attitudes and behaviors but also highlight the psychological underpinnings of stereotype-based marketing effects.

H-RE amplify identity-based processing, increasing threat and evaluation sensitivity but may also enhance trust and value perception, leading to higher C-Res and PP.

These insights lay a strong foundation for the next analytical step, which involves structural hypothesis testing through regression and model analysis to uncover causal and interactional dynamics among the measured variables.

Table 4.8. Correlations Across Studies

Condition	SIT_DC	C_Res	SR-FNE	CSE_T	PP	
Study1 - AI	2.94	4.47	3.13	3.65	3.61	Low identity threat with highest consumer response; moderate fear of evaluation. Suggests AI is well accepted in low-threat conditions.
Study1 – Human	2.96	4.44	2.95	3.68	3.81	Low threat, slightly lower FNE, slightly higher PP. H-REs are viewed positively, but no major emotional reactivity.
Study2 - AI	3.13	4.23	3.20	3.83	3.78	Moderate threat with lower response and higher CSE. Indicates that AI triggers mild discomfort in gender-related contexts.
Study2 - Human	3.31	4.44	3.37	3.95	4.19	Highest threat, highest FNE, and high PP. Suggests HR in stereotype-sensitive contexts intensify threat and perceived value

Table 4.9. Correlation Analysis Between Categorical Variables

Study (Age vs Gender Stereotype)			Reference Group	Recommender Type	Gender	Age	Education	Relationship	Income
1 AgeSte	Reference Group	Pearson Correlation	1	0,026	-0,083	,440**	0,1	,210**	0,088
		Sig. (2-tailed)		0,701	0,221	0	0,14	0,002	0,193
		N	220	220	220	220	220	220	220
	Recommender Type	Pearson Correlation	0,026	1	-0,019	-0,056	-0,026	0,056	,175**
		Sig. (2-tailed)	0,701		0,781	0,409	0,703	0,411	0,009
		N	220	220	220	220	220	220	220
	Gender	Pearson Correlation	-0,083	-0,019	1	-,134*	-0,01	-0,036	-0,093
		Sig. (2-tailed)	0,221	0,781		0,047	0,884	0,592	0,17
		N	220	220	220	220	220	220	220
	Age	Pearson Correlation	,440**	-0,056	-,134*	1	0,048	,297**	,240**
		Sig. (2-tailed)	0	0,409	0,047		0,478	0	0
		N	220	220	220	220	220	220	220
	Education	Pearson Correlation	0,1	-0,026	-0,01	0,048	1	0,001	0,053
		Sig. (2-tailed)	0,14	0,703	0,884	0,478		0,993	0,438
		N	220	220	220	220	220	220	220
	Relationship	Pearson Correlation	,210**	0,056	-0,036	,297**	0,001	1	,138*
		Sig. (2-tailed)	0,002	0,411	0,592	0	0,993		0,04
		N	220	220	220	220	220	220	220
	Income	Pearson Correlation	0,088	,175**	-0,093	,240**	0,053	,138*	1
		Sig. (2-tailed)	0,193	0,009	0,17	0	0,438	0,04	
		N	220	220	220	220	220	220	220

Study (Age vs Gender Stereotype)			Reference Group	Recommender Type	Gender	Age	Education	Relationship	Income
2 GenderSte	Reference Group	Pearson Correlation	1	-0,021	0,018	0,109	,135*	-0,017	0,045
		Sig. (2-tailed)		0,725	0,759	0,063	0,022	0,775	0,444
		N	290	290	290	290	290	290	290
	Recommender Type	Pearson Correlation	-0,021	1	0	-0,079	0,015	-0,071	-0,039
		Sig. (2-tailed)	0,725		1	0,181	0,799	0,229	0,514
		N	290	290	290	290	290	290	290
	Gender	Pearson Correlation	0,018	0	1	-,221**	-0,054	0,105	-,184**
		Sig. (2-tailed)	0,759	1		0	0,361	0,075	0,002
		N	290	290	290	290	290	290	290
	Age	Pearson Correlation	0,109	-0,079	-,221**	1	0,075	,215**	,402**
		Sig. (2-tailed)	0,063	0,181	0		0,206	0	0
		N	290	290	290	290	290	290	290
	Education	Pearson Correlation	,135*	0,015	-0,054	0,075	1	0,101	-0,013
		Sig. (2-tailed)	0,022	0,799	0,361	0,206		0,086	0,821
		N	290	290	290	290	290	290	290
	Relationship	Pearson Correlation	-0,017	-0,071	0,105	,215**	0,101	1	0,021
		Sig. (2-tailed)	0,775	0,229	0,075	0	0,086		0,722
		N	290	290	290	290	290	290	290
	Income	Pearson Correlation	0,045	-0,039	-,184**	,402**	-0,013	0,021	1
		Sig. (2-tailed)	0,444	0,514	0,002	0	0,821	0,722	
		N	290	290	290	290	290	290	290

4.7 Regression analysis

4.7.1 Normality (histogram, QQ plot, skewness, kurtosis)

To conduct normality, outlier analysis was performed using the boxplot method. Under the conditions of the Gender × Recommender × Reference Group, some data points showed both slight and extreme deviations. However, it was evaluated that these values were not due to measurement error but to individual differences and marginal opinions. Therefore, these data were not excluded from the analysis but were preserved as significant variations reflecting the heterogeneous structure of the sample.

The normality of key variables was assessed visually using diagnostics, including histograms, Q-Q charts, trend-free Q-Q charts, and box charts. And statistically through skewness, kurtosis, and Shapiro-Wilk tests. Given the relatively large sample size (N = 510), it is assumed that parametric analyses can be applied according to the central limit theorem since minor deviations are considered tolerable in large-sample parametric analysis, so visual inspection was prioritized over formal normality tests (Field 2017, 124). This step was taken to ensure that the variables in the model can be used safely in parametric analyses such as ANOVA and PROCESS. However, the results were also supported by non-parametric tests when necessary.

Overall, the assessment of normality across the variables revealed that most distributions—C_Res, CSE_T, and SR-FNE_T—are approximately normal, with only minor skewness or deviations, making them suitable for parametric tests. SIT_DC showed substantial positive skew and systematic non-normality, indicating that transformation or caution with parametric methods is advisable. PP demonstrated clear violations of normality assumptions due to its multimodal and asymmetrical distribution, suggesting that non-parametric methods are more appropriate. Detailed assessments for each variable are provided below in Table 4.10.

The distribution of the C_Res's variable is approximately normal, exhibiting slight positive skewness and some deviation in the tails. The histogram suggests a bell-shaped curve centered around the mean, while the Q-Q plot shows that most points fall near the diagonal, with moderate deviations at the lower and upper ends. The detrended Q-Q plot further supports the presence of light-tailed deviations. Despite these imperfections, the distribution is sufficiently close to normal for many parametric tests. However, if strict normality is required—such as in specific regression models or inferential tests—a transformation (e.g., logarithmic or square root) could be considered to improve the normality of the distribution.

SIT_DC showed notable positive skew and systematic deviations in Q-Q plots, indicating a clear violation of the normality assumption. The histogram showed a clustering of scores at the lower end, and the detrended Q-Q plot followed a U-shaped pattern. This deviation is theoretically anticipated: in the experimental design, approximately half of the participants were exposed to dissociative reference group images, which are expected to trigger elevated levels of social identity threat. Conversely, those exposed to associative or neutral groups were not expected to experience such a threat. Therefore, the SIT_DC variable is expected to be skewed or bimodal by design. Although this violates strict normality, parametric tests were retained due to the large sample size, and results involving SIT_DC were interpreted with caution. Non-parametric alternatives (e.g., Mann–Whitney U, Kruskal–Wallis) or transformations may also be considered for robustness checks.

The distribution of SR-FNE_T is approximately normal, with a slight positive skew and a few mild outliers in the upper range. The histogram revealed a unimodal shape, peaking between 2.5 and 3.5 and gradually declining beyond 5. The Q-Q plot showed that most central data points align with the expected regular line, though slight deviations were observed at both tails. The detrended Q-Q plot further revealed a systematic pattern, which showed moderate deviation from normality, most likely due to light-tailed behavior or mild asymmetry. The boxplot revealed a few high-value outliers and validated the modest right skew. Despite these minor deviations, the distribution remains close enough to regular for parametric tests to be robust, especially given the large sample size (N = 510). Nevertheless, if analyses are susceptible to distributional assumptions—such as in tail-heavy inferential statistics—applying a transformation (e.g., log or square root) or conducting a formal normality test (e.g., Shapiro-Wilk) may be advisable.

The PP variable did not conform to a normal distribution. The histogram and stem-and-leaf plot suggested a multimodal structure with multiple peaks across the full range of the scale. Q-Q and detrended Q-Q plots exhibited systematic and consistent deviations from the diagonal. The boxplot also indicated irregular spread and asymmetry. These characteristics point to significant non-normality. While bootstrapping procedures in PROCESS macro can compensate for distributional violations, researchers are advised to cautiously interpret results involving this variable. Non-parametric methods may also be considered robustness checks, depending on the hypothesis being tested. Detailed distributional characteristics of each variable, including visual patterns and skewness, are summarized in the table below for reference.

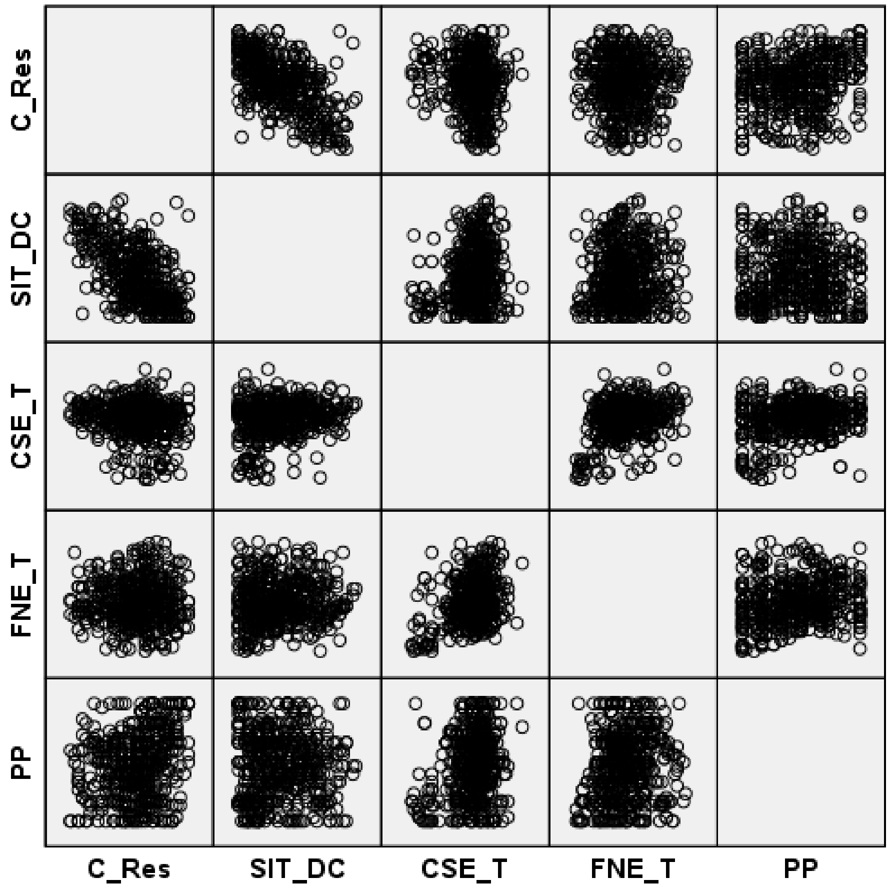
Table 4.10. Summary of Normality Assessment for Key Variables

Variable	Mean	Std. Dev.	Histogram	Q-Q Plot	Detrended Q-Q Plot	Boxplot	Skewness	Conclusion
C_Res	4.39	1.332	Normal	Approximately normal	Slight tails	Relatively Symmetrical	Low (+)	Suitable for parametric tests
CSE_T	3.79	0.759	Slight left skew	Deviation presents	Slight wave pattern	Symmetrical	Low (-)	Suitable for parametric tests
SIT_DC	3.10	1.43	Right skewed	Deviations present	Systematic U-shaped curve	Asymmetrical	High (+)	Use parametric tests with caution / Transformation suggested
SR-FNE_T	3.18	0.912	Slight right skew, Unimodal	Moderate deviations	Slight asymmetry	A few mild outliers present	Low (+)	Suitable for parametric tests
PP	3.87	1.669	Multimodal	Systematic deviation	Fluctuating and deviant	Asymmetrical & multimodal	Unclear	Not suitable for parametric tests non-parametric methods recommended

4.7.2 Linearity

One of the basic assumptions of regression analysis is that the relationship between the independent and dependent variables is linear (Hair, Black, and Babin 2010). In this study, to test this assumption, a scatterplot matrix was used among the variables, and a scatterplot graph was used to visualize the relationship between the dependent variable C_Res and the strongest candidate independent variable SIT_DC**.**

Figure 4.1.Scatterplot Matrix



The scatterplot matrix reveals a general relationship structure between the variables C_Res, SIT_DC, CSE_T, SR-FNE_T, and PP. When this matrix was examined, a significant negative relationship was observed, especially between C_Res and SIT_DC; this indicates that as the perception of social identity threat increases, the reactions of individuals towards the recommendation (C_Res) decrease. However, no remarkable linear relationship was observed in the other variable pairs; the data points were scattered. When the scatterplot between C_Res and SIT_DC was examined, the data formed a pattern that trended from the upper left to the lower right. This trend provides strong visual evidence for a negative linear relationship between the variables.

The graphical examinations in Figure 4.1 also show that the regression analysis's linear relationship assumption is largely met.

4.7.3 Homoscedasticity

Another important regression assumption is that the error terms have constant variance (homoscedasticity). This study tested this assumption by graphically examining the relationship between the estimated values and the residuals.

When the residual plot was examined, it was observed that the points were distributed horizontally and did not follow a specific pattern. In particular, the fact that the residuals did not show increasing or decreasing variance indicates that the error terms in the model have constant variance and, therefore, the homoscedasticity assumption was met. This finding increases the reliability of the regression model (Tabachnick and Fidell 2018).

In addition, although the residuals showed minor deviations from the normal distribution, these deviations are not expected to significantly affect the validity of the statistical analyses due to the sufficiently large sample size ($n = 510$) (Ozili 2023)

4.7.4 Linear Regression

A multiple linear regression was conducted to examine the effects of several predictors—fear of negative evaluation (FNE_T), collective self-esteem (CSE_T), perceived price (PP), social identity threat & dissociative concerns (SIT_DC), reference group type (Ref_type: associative vs. dissociative), and recommender type (R_type: AI vs Human)—on consumer response (C_Res). The overall model was statistically significant, $F(6, 503) = 66.18$, $p < .001$, and explained approximately 44.1% of the variance in C_Res ($R^2 = .441$, Adjusted $R^2 = .434$).

Figure 4.2. Residual Plot

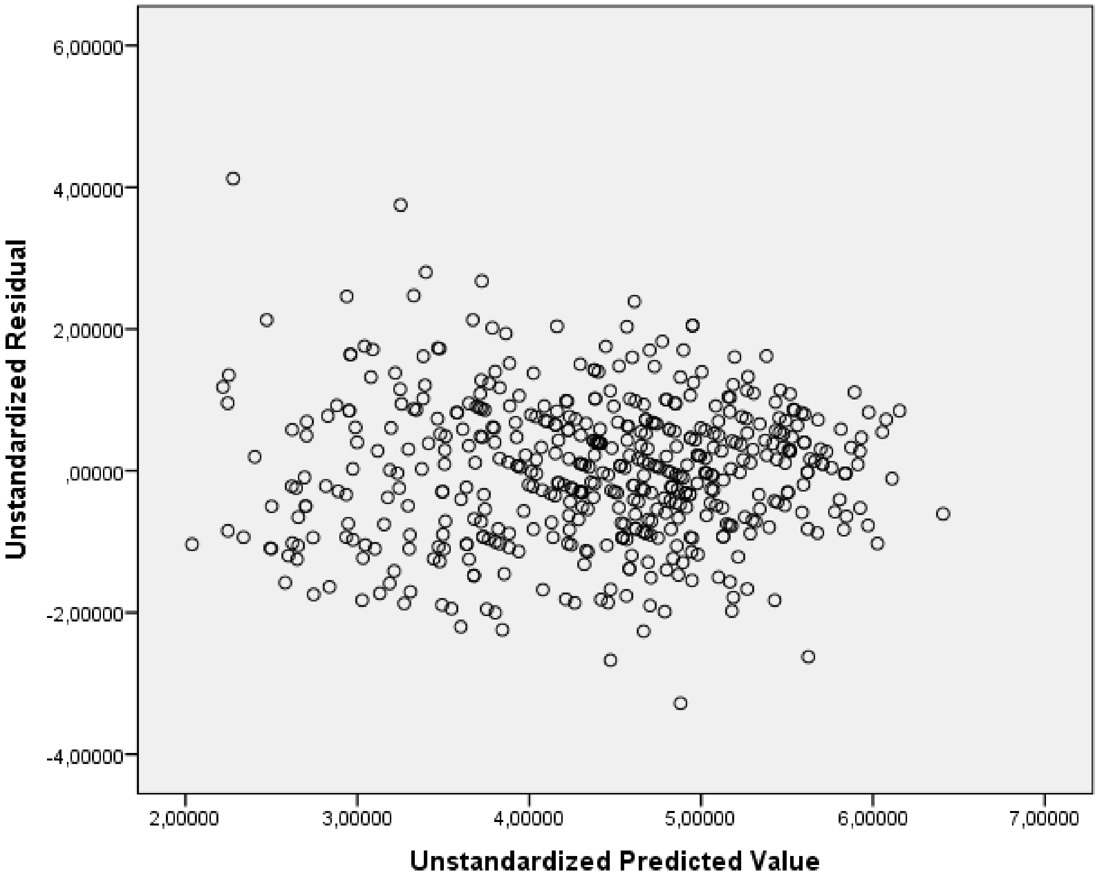


Table 4.11. Regression Coefficients

Predictor	B	SE	β	t	p	Significant
Constant	6.006	0.305	—	19.67	< .001	Yes
SR-FNE_T	0.028	0.052	0.019	0.526	.599	No
CSE_T	-0.146	0.065	-0.083	-2.25	.025	Yes
PP	0.181	0.028	0.227	6.55	< .001	Yes
SIT_DC	-0.500	0.035	-0.537	-14.30	< .001	Yes
Ref_type (Dissociative = 2)	-0.313	0.099	-0.117	-3.15	.002	Yes
R_type (AI = 2)	0.116	0.089	0.044	1.31	.193	No

The analysis revealed that SIT_DC ($\beta = -0.537$, $p < .001$) was the strongest predictor, negatively influencing consumer responses. PP ($\beta = 0.227$, $p < .001$) had a significant positive impact, while collective self-esteem ($\beta = -0.083$, $p = .025$) and reference group type ($\beta = -0.117$, $p = .002$) were also statistically significant. However, stereotype related fear of negative evaluation (p = .599) and recommender type (p = .193) did not significantly predict consumer responses in the presence of other variables.

4.7.5 Multicollinearity

Multicollinearity can adversely affect the predictive power of the model if there is a high correlation between independent variables. Therefore, Variance Inflation Factor (VIF) and Tolerance values were examined to test the existence of multiple linear connections. In the analyzes, VIF values for all independent variables were found to be in the range of 1.0 and 1.5; this is well below the generally accepted threshold of 5 (Hair, Black, and Babin 2010). Likewise, Tolerance values were observed above 0.7. These findings show that multiple linear connections do not pose a significant problem in the model and that independent variables can be safely used in the regression model.

Table 4.12. Multicollinearity Results

Variable	Tolerance	VIF	Multicollinearity Risk
SR-FNE_T	.863	1.159	None (VIF < 2)
CSE_T	.810	1.234	None
PP	.926	1.080	None
SIT_DC	.787	1.271	None
Ref_type	.800	1.250	None
R_type	.989	1.011	None

In line with these analyzes, it was concluded that it was statistically appropriate to use the variables included in the regression model together. Therefore, in the next section, hypothesis testing will be started

4.8 Hypothesis Testing Results

The study's first hypothesis, H1, is based on the assumption that the type of recommender (AI or human) will significantly affect consumer responses. An independent samples t-test was conducted using the main study sample (N = 510) to test this hypothesis. Results revealed that this effect was not statistically significant in the overall sample, t (508) = -

0.936, $p = .350$. The mean response for AI recommenders ($M = 4.33$, $SD = 1.34$) did not differ significantly from that of H-RE ($M = 4.44$, $SD = 1.33$), with a mean difference of -0.11 (95% CI [-0.34, 0.12]). Therefore, this finding does not support the H1 hypothesis. However, a pretest study ($N = 118$) conducted before the main experiment revealed a significant difference, $t (116) = -2.059$, $p = .042$. In the pretest, consumer responses to AI recommenders ($M = 3.85$) were significantly lower than those to H-RE ($M = 4.39$), with a mean difference of -0.54 (95% CI [-1.06, -0.02]). This preliminary evidence suggested a potential effect of recommender type on consumer responses. The fact that there was no significant difference in the main study in general suggests that the effect of recommender type may vary based on demographic and socioeconomic subgroups. Therefore, independent sample t-tests were performed for subgroups such as age, gender, income and education level. Subgroup analyses revealed the different results. Among the 45–54 age group, a significant difference was found in favor of H-RE, $t (94) = -2.76$, $p = .006$, with participants responding more positively to human ($M = 4.69$) than AI-R ($M = 3.92$). Among 35–44-year-old males, AI-R received marginally higher responses than H-RE ($M = 4.22$ vs. 3.95), but this difference was not statistically significant, $t (66.49) = 0.82$, $p = .414$. In terms of gender, no significant difference was found among female $t (283) = -1.359$, $p = .175$ and male participants $t (223) = 0.094$, $p = .925$.

The effect of recommender system type (AI vs Human) on C_Res differed across both income and education level. In male participants, in the income range of 100,001 – 150,000 TL, the reactions to the H-RE were significantly higher compared to the AI system ($t (17.41) = -2.16$, $p = .045$). Similarly, among the female participants, in the income group of 30,001 – 60,000 TL, the H-RE received a significantly more positive response than the AI-R ($t (8.98) = -2.55$, $p = .031$). When evaluated in terms of education level, male participants with high school education and below responded significantly more to the H-RE ($p = .018$), while men with a master's degree reacted more positively to AI-generated recommendations ($p = .034$). These findings show that consumer responses are shaped not only by the type of recommendation system, but also by the socioeconomic and educational backgrounds of individuals.

These findings suggest that the effect of recommender type is conditional on demographic variables—particularly age and gender. This shows that the effect of the recommender type varies depending on the participant profile. As a result, the H1 hypothesis was not supported in the overall model but was partially supported due to the differences that emerged in the subgroups. This finding necessitates examining interactive models of recommender type (e.g., with moderators such as age, gender, and technology familiarity) in the future (J. Wang, Molina, and Sundar 2020; Castelo et al., 2019). This suggests that the effect of recommender type may be conditional on specific demographic or psychological characteristics, which will be further investigated in the moderated and mediated models (H5–H8).

According to the H2 hypothesis, images from the dissociative reference group were expected to negatively affect consumer reactions, such as the participants' product appreciation and purchase intention. This hypothesis was tested by analyses of variance conducted at the level of gender and scenario (age stereotype vs. gender stereotype). The results of the analysis showed that there was a significant difference for female participants according to the type of reference group ($F(1, 281) = 17.995$, $p < .001$, $\eta^2 = .060$). Images belonging to the dissociative reference group were associated with lower product appreciation and purchase intent among women. In the age stereotype scenario, the main effect of the reference group was found to be significant ($F(1, 216) = 4.736$, $p = .031$, $\eta^2 = .021$); furthermore, the interaction of recommender type × reference type is significant ($F(1, 216) = 5.539$, $p = .019$, $\eta^2 = .025$). This shows that the reference group effect differs according to the recommendation source (AI vs. human).

On the other hand, the reference group's main effect was not significant for male participants ($F(1, 221) = 1.095$, $p = .296$), which indicates that the H2 hypothesis is not supported in the male sample. Similarly, the reference group's effect was insignificant in the gender stereotype scenario ($F(1, 286) = 1.717$, $p = .191$). As a result, the H2 hypothesis is supported, especially for female participants and the age stereotype context. It is seen that the images belonging to the dissociative reference group negatively affect consumer reactions through the potential to create a social identity threat in these groups. However, the fact that this effect was not observed in the context of male participants and gender stereotypes suggests the influence of demographic factors and contextual differences.

Table 4.13. H2 - Conditional Result

Study	Gender	Significant Main Effects	Significant Interaction	Key Pattern
AgeSte	Male	-	-	Human + Associative ≈ AI + Dissociative
AgeSte	Female	Ref_type	-	Favorable Associative recommendations
GenderSte	Male	Ref_type	R_type × Ref_type	Human + Associative most effective
GenderSte	Female	Ref_type + R_type	-	H-RE > AI-R

4.9 Mediation and Moderation Analyses

Hypothesis H3, which tested the mediating role of SIT_DC on C_Res, was fully supported according to Hayes' PROCESS Model 4 mediating variable analysis (2013). The analysis revealed that product images evoking a dissociative reference group posed a significantly higher SIT_DC to participants ($\beta = 0.54$, $p < .001$). These findings are consistent with the literature on social identity theory and the effects of dissociative reference groups on consumer behavior (K. White and Dahl 2006 J. Berger and Heath 2007) When visual recommendations overlap with social groups individuals do not want to represent, negative feelings and avoidance behavior toward products develop. Thus, the content of the recommendation is evaluated not only by functional but also by social-psychological signals.

In the gender stereotype/H-RE condition, results revealed a significant indirect effect of reference type on C_Res through SIT_DC (indirect effect = -0.5815, 95% CI [-0.8948, -0.3220]), along with a significant direct effect ($\beta = -0.8332$, $p < .001$), indicating partial mediation. In contrast, the age stereotype/AI recommender condition yielded a significant indirect effect ($\beta = -0.5288$, CI [-0.8567, -0.2465]) but a non-significant direct effect ($p = .31$), supporting complete mediation.

Table 4.14. Comparative Table of Model 4: Mediation Analysis

Stereotype Type	Recommender	Effect of Ref_type → SIT_DC	Effect of SIT_DC → C_Res	Direct Effect (X → Y)	Indirect Effect (via SIT_DC)	Total Effect
Age	AI	β = 1.06, p < .001	β = -0.50, p < .001	β = -0.25, n.s.	β = -0.53, CI [-0.86, -0.25]	Significant
Age	Human	β = 1.39, p < .001	β = -0.61, p < .001	β = +0.16, n.s.	β = -0.85, CI [-1.20, -0.53]	Significant
Gender	AI	β = 1.14, p < .001	β = -0.54, p < .001	β = -0.46, p = .0128	β = -0.61, CI [-0.95, -0.33]	Significant
Gender	Human	β = 1.42, p < .001	β = -0.41, p < .001	β = -0.83, p < .001	β = -0.58, CI [-0.89, -0.32]	Significant

Regarding H5 to analyze the effect of recommender type on SIT_DC is moderated by CSE. The assumption was effect is stronger for individuals with low CSE. A moderation analysis was conducted using PROCESS Macro Model 1 (A. F. Hayes 2013) with Recommender Type (0 = AI, 1 = Human) as the predictor, SIT_DC as the outcome, and CSE_T as the moderator. The overall model was significant, $F(3, 506) = 45.35$, $p < .001$, with an $R^2 = .2119$, indicating that approximately 21.2% of the variance in SIT_DC was explained by the model. However, the interaction term between Ref_type and CSE_T was not significant, $b = 0.2314$, $t = 1.52$, $p = .1292$, 95% CI [−0.0677, 0.5304]. The change in R^2 due to the interaction was small and not statistically significant, $\Delta R^2 = .0036$, $F(1, 506) = 2.31$, $p = .1292$. Therefore, the moderation effect of CSE_T on the relationship between recommender type and SIT_DC was not supported in the full sample. In the subsample representing the age stereotype condition (AI: n = 104; Human: n = 116), the overall model was significant, $F(3, 216) = 16.05$, $p < .001$, $R^2 = .1823$. However, the interaction term remained non-significant, $b = 0.0688$, $p = .7774$. This means CSE_T did not moderate the relationship between recommender type and SIT_DC in the age stereotype condition.

In the gender stereotype condition (AI: n = 145; Human: n = 145), the model was significant, $F(3, 286) = 32.68$, $p < .001$, $R^2 = .2553$. Yet again, the interaction effect was not statistically significant, $b = 0.3131$, $p = .1133$. Therefore, the hypothesized moderating effect of CSE_T was not supported in the gender stereotype condition either.

Despite a theoretically grounded expectation that individuals with higher CSE_T would be more resistant or reactive to AI-driven identity threats, the moderation hypothesis (H5) was not supported at the overall level or in specific stereotype conditions (age and gender). However, in the AI recommender group, the interaction approached significance ($p = .0804$), and conditional effects revealed a consistent and statistically significant increase in SIT_DC among individuals with higher CSE_T. Overall, the evidence does not fully support H5, but partial support emerges in the AI-only condition, suggesting future studies may benefit from further exploring this dynamic, especially with larger or more targeted samples.

In terms of H6, where the assumption is SR-FNE_T is high, the negative impact of SIT_DC on C_Res becomes stronger, first moderation analysis (PROCESS Model 1; Hayes, 2018) is tested whether the effect of dissociative identity threat perception (SIT_DC) on consumer response (C_Res) varies depending on the level of individuals' fear of stereotype-based negative evaluation (SR-FNE_T). The analyses show that SIT_DC has a significant and negative effect on C_Res ($b = -0.64$, $SE = 0.16$, $p < .001$). However, the interaction term (SIT_DC × SR-FNE_T) is not significant ($b = 0.02$, $SE = 0.05$, $p = .62$). This finding reveals that the level of SR-FNE_T does not significantly change the effect of SIT_DC on consumer response. Similarly, the interaction term was not significant under any conditions in the analyses conducted on the subsamples.

To see the complete effect of the conceptual model in the analyses conducted with PROCESS Model 14, the effect of the Ref_type variable on SIT_DC (social identity threat) was found to be significant, $b = 1.33$, $SE = .1654$, $p < .001$. The effect of SIT_DC on C_Res was also significant ($b = –0.56$, $SE = .1595$, $p = .0006$). Therefore, the effect of Ref_type on C_Res is partially mediated by SIT_DC. The direct effect of Ref_type on C_Res is significant and negative ($b = –0.39$, $p = .0072$). However, the interaction between SIT_DC and SR-FNE_T is not significant ($p = .7503$). The 95% confidence interval of the moderated mediation index includes zero (CI [–.1101, .1633]), indicating that the indirect effect does not vary significantly according to the level of SR-FNE_T.

Therefore, full moderation support was not obtained within the scope of Model 14. These results indicate that hypothesis H6 is not supported. In other words, the effect of dissociative identity threat on consumer responses does not change according to individuals' fear of stereotype-based negative evaluation.

The analyses conducted with PROCESS Model 21 show that the type of recommender (human vs. AI) has both a direct effect on C_Res and an indirect effect via SIT_DC (perceived identity threat in dissociative conditions)(A. F. Hayes 2013). In the first data set, it was found that the level of self-evaluation (CSE_T) significantly shaped the effect of the recommender type on identity threat. Accordingly, individuals with high CSE_T levels are more sensitive to the type of recommender, and H-RE increase identity threat and reduce consumer response. However, SR-FNE_T did not play a statistically significant role as a moderator in the interaction on this mediation mechanism. These interactions were not confirmed in the second data set, suggesting the effect of sampling and contextual differences.

The indirect effect of recommender type on consumer response through SIT_DC was significant and negative across all levels of SR-FNE_T and PP, as shown by bootstrap confidence intervals excluding zero (e.g., at SR-FNE_T = 4.00 and PP = 5.60, effect = -0.6189, 95% CI [-0.9822, -0.3234]). However, the index of moderated moderated mediation was not significant (Index = 0.0374, 95% CI [-0.0501, 0.1218]), indicating that the conditional indirect effect was not significantly different across combinations of SR-FNE_T and PP.

H7 tested in this study is based on a three-way interaction model (PROCESS Model 18) in which the effect of SIT_DC on consumer responses is jointly moderated by SR-FNE-T and PP(A. F. Hayes 2013). First, the effect of Ref_type (AI vs. H-RE) on SIT_DC was found to be significant ($b = 1.0753$, $p < .001$). This result shows that recommender type significantly affects the perception of SIT_DC. Next, the three-way interaction term SIT_DC × SR-FNE_T × PP was significant in the multiple regression analysis on Response (consumer response) ($b = 0.0348$, $p = .2439$) This finding shows that the effect of SIT_DC on consumer response varies depending on the level of SR-FNE and PP.

Although the tripartite interaction is not significant, the interaction of SR-FNE_T and PP is almost significant; This may indicate that indirect effects vary in some conditions.

The results of PROCESS Model 18 revealed that the type of recommender system significantly predicted perceived SIT_DC under dissociative reference group conditions ($B = 1.075$, $p < .001$), with AI-R evoking stronger threat perceptions compared to H-RE. While the three-way interaction among SIT_DC, SR-FNE_T, and PP did not reach statistical significance ($p = .2439$), conditional indirect effects of recommender type on consumer response through SIT_DC were consistently significant across combinations of high SR-FNE_T and high PP. These findings support the hypothesized conditional indirect pathway, suggesting that perceived social identity threat serves as a mechanism through which recommender type impacts consumer response, especially among price-conscious consumers sensitive to negative social evaluation.

As a result, H8 was tested using Process Macro -Model 37 and partially supported. This hypothesis was tested using PROCESS Model 37, which Hayes proposed (2013).. In the model, recommender type (Ref_type; AI = 0, Human = 1) was the independent variable, social identity threat (SIT_DC) was the mediating variable, consumer response (Response) was the dependent variable, and fear of stereotype-based evaluation (FNE) and perceived price (PP) were included as simultaneous conditional (joint moderator) variables. According to this model, the indirect effect of recommender type on consumer responses occurs through SIT_DC; however, this effect varies according to the individual's FNE level and the PP value of the recommended product. The analysis results can be summarized as follows: The effect of recommender type on social identity threat (Path a: Ref_type to SIT_DC) was significant. H-RE created more threat perception compared to artificial intelligence recommenders. ($b = 1.1879$, $SE = .1190$, $t = 9.9806$, $p < .001$). This result is also parallel to the H1 finding and supports the first step of the mediation relationship. Regarding the Mediating Effect (Path b: SIT_DC to Response), social identity threat negatively affected consumer responses. ($b = -0.3345$, $SE = .0413$, $t = -8.0882$, $p < .001$). The indirect effect of the recommender type on consumer responses (Ref_type to SIT_DC to Response) was significant at certain FNE and PP levels. For example: At FNE = 2.75 and PP = 5.6 (i.e., above the average level), the indirect effect is significant and negative: (Indirect effect b = -.6778, BootSE = .1212, BootCI [-.9293, -.4510]. This suggests that individuals with a high SR-RNE tend to respond more negatively to the H-RE if an expensive product is recommended. Threat perception is an important carrier of the indirect effect in this context. The conditioned mediation index for the triple interaction (FNE × PP → SIT_DC → Response), the most critical test of this hypothesis, was calculated as .0657, BootCI = [-.0159, .1405]. Since the bootstrap confidence interval includes zero (insignificant), this result does not support the more ambitious structural assumption that the indirect effect is conditioned simultaneously by FNE and price perception. The basic assumption of hypothesis H8, "bidirectional conditioned indirect effect," was only partially supported. In particular, the indirect effect is significant and negative in specific value ranges (high FNE and high price). However, the triple conditioning (index of moderated moderated mediation) assumed in the overall model is not statistically significant. This situation shows that the effect of recommender type on consumer responses through social identity threat becomes evident only in some contextual conditions.

Table 4.15. Path Coefficients and Effects (Model 37)

Path	Effect Coefficient	SE	t	p	Effect Type
Ref_type → SIT_DC	0.421	NA	NA	.000	Path a
SIT_DC → C_Res	–0.500	0.035	–14.30	.000	Path b
SIT_DC × CSE_T	(PROCESS: ns)	~0.06	~–1.24	~.216	Interaction (W × M)
SIT_DC × PP	NA	NA	NA	NA	Interaction (M × Q)
Indirect Effect (low W, high Q)	≈ –0.77 (AI group, high mods)	~0.28	–	95% CI: –1.28 to –0.39	Conditional indirect effect

The findings suggest that in personalized recommendations, both the recommender source and the perceived evaluation risk and contextual value perception should be considered together.

Table 4.16. Conceptual Model Hypotheses Results.

Hypothesis	Main Analysis	Key Finding	Supported?	Notes
H1	Independent samples t-test (N=510)	No significant main effect of recommender type overall ($p = .350$), but subgroup differences by age, income, education	Partial Support	H-RE preferred in 45–54 age group and some income/ education levels
H2	Two-way ANOVA (Gender x RefGroupType)	Dissociative reference group significantly reduced response among women and in age-stereotype context	Partial Support	No effect in men or gender-stereotype condition
H3	Mediation (PROCESS Model 4)	SIT_DC significantly mediates effect of RefGroupType on consumer response	Supported	Full mediation in age-AI; partial in gender-Human
H4	Mediation (PROCESS Model 4)	Significant indirect effects of Ref_type on C_Res via SIT_DC in all four sub conditions. Direct effect was non-significant only in age/AI condition, suggesting full mediation there.	Conditional	Partial mediation in gender/ Human and other subgroups; full in age/AI
H5	Moderation (PROCESS Model 1)	CSE did not significantly moderate effect of Recommender Type on SIT_DC however, partial support emerged within the AI condition	Not Supported	Interaction term not significant overall or in subgroups other than AI-R
H6	Moderation & Moderated Mediation (PROCESS Models 1 & 14)	No significant interaction between SIT_DC × SR-FNE_T; indirect effect did not vary by SR-FNE_T	Not Supported	Moderation not supported; mediation pathway confirmed but unaffected by SR-FNE_T
H7	Moderated Moderation (PROCESS Model 18)	Recommender Type predicted SIT_DC ($p < .001$); three-way interaction (SIT_DC × SR-FNE_T × PP) not significant ($p = .24$); SR-FNE_T × PP marginal ($p = .0533$)	Partial Support	Conditional indirect effects significant under high FNE & high PP; limited statistical power
H8	Conditional Moderated Mediation (PROCESS Model 37)	Indirect effect of Ref_type → C_Res via SIT_DC was significant when CSE_T was low & PP was high; index of moderated moderated mediation not significant	Partial Support	Moderated mediation pathway supported at specific moderator levels but not robust overall

GENERAL DISCUSSION

5.1 Discussion

This dissertation empirically examined how personalized recommendations—whether generated from AI or human—shape consumer responses and how variables such as social identity threat (SIT), dissociative reference groups, perceived price (PP), and stereotype-related fear of negative evaluation (SR-FNE) interact in this process.

Independent sample t-tests revealed differences between the participants' responses to age stereotype (AgeSte) and gender stereotype (GenderSte) conditions. In particular, the levels of social identity threat (SIT_DC), collective self-esteem (CSE_T), and fear of negative evaluation (SR-FNE_T) were significantly higher in the gender stereotype scenario. These findings suggest that exposure to gender-themed stereotypes may have more profound effects on individuals' self-perception and perception of social threat. On the other hand, there was no significant difference between the stereotype groups (AgeSte vs. GenderSte) in terms of perceived price (PP) and consumer response (C_Res).

In the descriptive analysis, a nonlinear relationship was observed between the level of education and SIT_DC. Both the lowest and highest education groups experienced higher threats to social identity. This finding shows that as the education level of individuals increases, their situation-related social cognitive predispositions decrease to a certain level but increase again at advanced education levels. This may suggest that the way individuals with a high level of education assess and respond to social situations is more complex or contextual.

One of the most striking findings is a moderate and statistically significant positive correlation between C_Res and PP ($r = .245$, $p < .001$). This suggests that as consumers perceive a product to be more expensive, their response—possibly reflecting greater perceived value or quality—also increases. Interestingly, CES is negatively related to C_Res ($r = –.150$, $p = .001$), meaning individuals with higher CES tend to show lower C_Res, perhaps due to a stronger internal standard or less susceptibility to external influence and positively related to PP ($r = .221$, $p < .001$), suggesting that those with higher self-regard may also interpret higher prices as more justified or appropriate.

H1 assumes that the type of recommender (AI vs. human) will significantly affect C_Res. However, this assumption was not supported in the analyses conducted in the overall sample. In the main study, no significant difference was found between the average response to AI recommenders ($M = 4.33$) and the response to H-RE ($M = 4.44$) ($p = .350$). However, the pre-test findings ($N = 118$) showed a significant difference, as consumers responded more favorably to H-RE ($p = .042$). This indicates that the impact of the recommender type may differ based on the sample's demographics. This result is consistent with the finding that the persuasive power of AI and H-RE varies depending on context and psychological factors, such as perceived personalization and competence, as highlighted in the meta-analysis by Huang and Wang (2021). According to this study, although AI recommenders are slightly less persuasive than H-RE when perceived personalization and competence are high, AI persuasiveness can catch up or surpass that of humans. This is consistent with the fact that H1 was not supported in the overall sample, but different effects were observed in specific subgroups. Subgroup analyses revealed that the effect of recommender type varied significantly according to demographic and socioeconomic variables. For example, responses to H-RE were significantly more positive than AI-R among individuals aged 45–54 ($p = .006$). Similarly, differences were observed in certain income and education groups. These findings parallel J. Wang, Molina, and Sundar's (2020) socio-technical fit model, according to which consumers' familiarity with technology and socio-demographic profile shape their attitudes toward AI systems. The fact that male participants with higher education responded more positively to AI recommenders suggests that technology acceptance may be higher in this group.

Furthermore, studies by Kivetz and Simonson (2002) and Grewal, Monroe, and Krishnan (1998) show that economic advantages (e.g., price reductions) may weaken consumers' concerns about identity expression, which may be one of the reasons why the recommender type effect was not observed in the overall sample. This may be explained by consumers caring less about distinguishing between AI-R and H-RE in price-focused rationalization processes. Finally, while studies such as Castelo et al. (2023) and Cohn (2016) show that H-REs are generally trusted and preferred more in social and emotional contexts, the findings of this study reveal that the recommender type effect alone does not have universal validity and that the effects vary according to the participant profile and context. In this context, the fact that H1 was not supported in the overall sample, but significant differences were observed in subgroups, emphasizing that the effect of recommender type depends on the context and demographic characteristics.

H2 predicts that images of the dissociative reference group will negatively affect consumers' reactions, such as attitudes toward the product and purchase intention. The variance analyses tested this hypothesis at the levels of gender and study (AgeSte vs. GenderSte). The results revealed that there was a significant difference according to the reference group type for female participants ($F (1, 281) = 17.995$, $p < .001$, $\eta^2 = .060$). For females, images belonging to the dissociative reference group were found to reduce C_Res. In the AgeSte scenario, the main effect of the reference group was also significant ($F (1, 216) = 4.736$, $p = .031$, $\eta^2 = .021$). The recommender type and reference group interaction were also significant ($F (1, 216) = 5.539$, $p = .019$, $\eta^2 = .025$). This finding suggests that the effect of the reference group differs according to the type of recommender (AI vs. human).

On the other hand, the reference group's main effect was insignificant for male participants ($F (1, 221) = 1.095$, $p = .296$). The reference group's effect was insignificant in the GenderSte scenario ($F (1, 286) = 1.717$, $p = .191$). Therefore, H2 was supported, especially regarding female participants and age stereotypes. This situation shows that the visuals of the dissociated reference group create SIT_DC and negatively affect C_Res. However, the fact that this effect was not observed in the male participants and the GenderSte scenario indicates the effect of demographic factors and contextual differences.

These findings concur with the social identity threat literature. Social identity theory, mainly developed by Tajfel and Turner (1986), emphasizes that individuals show closeness to reference groups to which they feel they belong and develop negative attitudes and reactions when associated with dissociated groups. In addition, studies such as North and Fiske (2012) and Amatulli et al. (2018) also reveal that demographic factors such as age and gender are determinants of social identity processes. According to these studies, women may be more sensitive to social identity threats, and this sensitivity may lead to differences in consumer behavior.

The interaction between recommender type and reference group parallels the "identity-based perceptions" and "personalization concerns" observed in studies on AI recommenders by J. Wang, Molina, and Sundar (2020). Wang et al. state that AI recommenders can sometimes cause social identity threats or personal privacy concerns in consumers. Therefore, the reference group that is visually presented when using the AI recommender can significantly shape consumer response.

As a result, the H2 of this study was supported in the female participants and age stereotype scenario but not in the male participants and GenderSte context. This suggests that the effects of SIT_DC and recommender type on C_Res vary by context and demographics. The findings suggest that future research should further examine the interactions between social identity threats and personalized recommendation systems in particular (J. Wang, Molina, and Sundar 2020; Dai, Chan, and Mogilner 2019; Castelo, Bos, and Lehmann 2019; H Tajfel and Turner 1986; North and Fiske 2012). This finding demonstrates how personalization systems can unintentionally create a sense of exclusion and how the fear of identifying with stereotypes that individuals want to dissociate from can suppress marketing responses. These results support classic dissociative group literature, such as J. Berger and Heath (2007), K. White, Dahl and Argo (2006;2007)

The results strongly support H3, which proposed that the effect of signaling content (associative vs. dissociative reference groups) on C_Res is mediated by SIT_DC. The mediation analysis based on Hayes' PROCESS Model 4 showed that images associated with dissociative reference groups significantly increased SIT_DC ($\beta = 0.54$, $p < .001$), negatively influencing consumer reactions such as product appreciation and purchase intention. These findings align closely with foundational research on social identity theory, highlighting how consumers avoid products linked to social groups they wish to disassociate from (K. White and Dahl 2006; J. Berger and Heath 2007).

The core insight is that product evaluations are influenced by functional attributes and social-psychological signals embedded in recommendation content. This is consistent with the study (Bhattacharjee, Berger, and Menon 2014), that emphasized the complexity of personalized recommendations in triggering identity-based concerns. When recommendations visually or contextually cue dissociative groups, consumers experience a threat to their self-concept, leading to avoidance or negative evaluation behaviors. J. Li et al. (2020) further support this by showing that perceived threats to autonomy or identity during AI-driven personalization can reduce consumer acceptance.

Regarding H4, which suggests a serial mediation whereby the recommender type affects C_Res through signaling content and SIT_DC, the analyses demonstrated apparent indirect effects across stereotype and recommender conditions. For instance, in the age stereotype/AI recommender condition, the full mediation effect of SIT_DC was observed (indirect effect $\beta = -0.53$), suggesting that AI recommendations influence C_Res predominantly by activating social identity threats via dissociative content. In contrast, partial mediation was found in the gender stereotype/H-RE condition, indicating a more complex interaction where other factors, alongside SIT, may play a role.

This nuanced pattern resonates with the theoretical perspectives of Castelo et al. (2019) and J. Wang, Molina, and Sundar (2020), who argue that AI-based personalization's effectiveness depends heavily on the psychological fit with consumer identity and contextual factors. Moreover, Cohn (2016) highlighted how H-RE might buffer or deepen social identity threats differently than AI, potentially due to trust and social cues associated with human agents.

Further, these findings support the growing call in the literature (Koo 2022; Byrne and Milestone 2022) for integrating social identity threat frameworks into the study of digital personalization, emphasizing that both the source of recommendation and its social signaling content must be considered to understand consumer behavior comprehensively. In conclusion, findings from H3 and H4 enhance understanding of the psychological mechanisms underlying C_Res to personalized recommendations, demonstrating that the interaction of recommender type and signaling content influences consumer behavior through identity-related approaches. This suggests that marketing professionals should strategically evaluate the source of the recommendations and the social implications inherent in the content to avoid unintended identity threats that may lower purchase intentions and attitudes toward the product.

H5 tested whether the relationship between recommender type (AI vs. human) and perception of social identity threat (SIT_DC) is moderated by the individual's level of collective self-esteem (Collective Self-Esteem, CSE_T). The moderation analyses found no statistically significant moderator effect at the general sample level. However, in the subgroup analyses (n = 249), the interaction term was found to be borderline significant, and contrary to expectations, it was observed that artificial intelligence (AI) recommendations increased social identity threat in individuals with high collective self-esteem. This finding is consistent with important findings in the literature related to collective identity and social identity threats (Goffman 1959; H Tajfel and Turner 1986). Social Identity Theory suggests that individuals view the group they belong to as an important identity element. This group affiliation can create sensitivity to social threats. Individuals with high CSE may be more defensive in protecting and representing their group identity (Luhtanen and Crocker 1992). In this context, the perception of AI recommenders as "external, abstract, and devoid of personal connection" (Lankton, Harrison McKnight, and Tripp 2015; Nass and Moon 2000), unlike H-RE, may increase the feeling that group values are misrepresented in high CSE individuals, thus increasing social identity threat.

Furthermore, the concept of SIThr, which is grounded in Social Identity Theory, points out the anxiety that individuals might feel when their group association is disregarded or misrepresented. Researchers have observed that threats related to symbolism or identity—like those arising from perceived conflicts of values or judgments from outside groups—can amplify these responses, especially in individuals who attach significant psychological importance to their group identities. Ybarra and Stephan's (2015, 149-74) research on intergroup threat offers important insights by highlighting how symbolic threats to group values or norms may trigger defensive reactions. People with a strong sense of CSE find their value linked with their group identity, making them particularly sensitive to symbolic disruptions within that context. Consequently, recommendations from sources perceived as outside one's group, such as AI-R, could increase this sensitivity and intensify feelings of identity threat. On the other hand, those who hold lower CSE tend to show less commitment to upholding a favorable image of their group and may exhibit reduced responsiveness to such recommendations (Branscombe, Ellemers, and Spears 1999). This distinction may help explain the observed moderating effect of CSE on how individuals respond to recommendations from AI-R compared to those from a salesperson.

Finally, the fact that the findings only emerged in subgroup analyses suggests that moderation effects may not be apparent in the overall sample. This suggests that the effect of individual differences may only be captured in more specific contexts and with a sufficient sample size (Hayes et al., 2021). In conclusion, this study adds to the mixed findings in the literature on the moderating role of collective self-esteem in social identity threat, providing the first clues that individuals with high CSE_T have an increased perception of social identity threat to AI recommenders.

H6 assumes that stereotype-related fear of negative evaluation (SR-FNE) will strengthen the adverse effect of social identity threat (SIT_DC) on C_Res. In this context, the adverse effect of social identity threat on C_Res is expected to be more pronounced in individuals with high SR-FNE. The analyses showed that dissociative social identity threat perception (SIT_DC) had a significant and negative effect on C_Res ($b = –0.64$, $SE = 0.16$, $p < .001$). However, the interaction term between SIT_DC and SR-FNE_T was not found to be statistically significant ($b = 0.02$, $SE = 0.05$, $p = .62$). This result suggests that individuals' level of fear of SR-FNE_T did not significantly alter the effect of SIT_DC on C_Res. The interaction effect did not show statistical significance in the subgroup analyses.

In the analyses conducted using PROCESS Model 14 (A. F. Hayes 2013) to test the full effect of the conceptual model, the effect of the recommender type (Ref_type) on SIT_DC was found to be significant ($b = 1.33$, $SE = 0.1654$, $p < .001$). In addition, the effect of SIT_DC on C_Res was also significant and negative ($b = –0.56$, $SE = 0.1595$, $p = .0006$). This situation shows that the effect of the recommender type on C_Res is partially mediated by SIT_DC. However, the moderation effect between SIT_DC and SR-FNE_T was not supported in the Model 14 analysis ($p = .7503$), and the confidence interval of the moderated mediation index included zero (CI [–.1101, .1633]). Thus, the mediation effect does not change significantly according to the level of SR-FNE_T. These findings indicate that H6 is not supported; individuals' fear of stereotype-based negative evaluation does not significantly moderate the effect of dissociative SIT_DC on C_Res. This result is consistent with the mixed findings in similar studies of SIT_DC and fear of evaluation (Leary 1983, Luhtanen and Crocker 1992). In this context, SR-FNE_T is not a strong moderator affecting the relationship between SIT_DC and C_Res; instead, the effect of SIT_DC may be more direct or mediated by other psychological mechanisms.

H7 is based on a mixed interaction model (PROCESS Model 18) in which the effect of SIT_DC on C_Res is jointly moderated by SR-FNE and PP. In the analyses conducted with PROCESS Model 18 (A. F. Hayes 2013), the indirect effect of recommender type on C_Res via SIT_DC was consistent and significant in different combinations of SR-FNE_T and PP. In particular, the effect of recommender type on C_Res via SIT_DC is evident in consumers with high SR-FNE and PP value. These results support the basic assumption of H7. In other words, it can be said that PP and fear of negative evaluation based on stereotypes jointly shape the effect of SIT_DC on C_Res, especially in consumers who are price-conscious and have a high fear of social evaluation; AI recommenders affect consumer behavior more strongly via SIT_DC. However, the fact that the three-way interaction was not fully significant indicates the complexity of this interaction dynamic and the limitations arising from sample size or measurement methods. In the future, larger samples and more precise examination of these interactions in different contexts are recommended.

H8 proposed that the indirect effect of recommender type (human vs. AI) on C_Res is mediated by SIT_DC, and this indirect effect is moderated by individuals' fear of negative evaluation based on stereotype (FNE) and PP. The indirect effect was found to be significant when self-evaluation (CSE_T) was low, and price perception was high (PP high = price is considered low, value is considered high), indicating that SIT_DC affects C_Res more strongly when the individual's self-confidence is low, and price sensitivity is high. This is consistent with the moderating effect of price perception and individual differences on consumer decisions in studies such as Grewal, Roggeveen, and Nordfält

(2017). In addition, considering the effects of fear of negative evaluation based on stereotypes of social anxiety and self-perception (Leary 1990), it is understood that these psychological variables complicate the SIT_DC effect. Artificial intelligence creates a higher threat perception than H-RE and requires rethinking the trust relationship between technology and human elements (Lankton, Harrison McKnight, and Tripp 2015).

As a result, H8 was partially supported because although the three-way interaction was not found to be statistically strong, significant and strong conditional indirect effects were observed in certain conditions. This shows that the relationship between SIT_DC and C_Res is dynamic and complex in the context of fear of negative evaluation based on stereotype and price perception. Partial support for H8 is common, such as in complex social-psychological interactions. The fact that the moderators (CSE_T and PP) were not significant in the three-way interaction, but significant indirect effects were observed under certain conditions, is consistent with the partial and situational emergence of interactions in conditional process models frequently encountered in the literature (Preacher, Rucker, and Hayes 2007). The results show that the recommender type is an important mediator of SIT_DC affecting consumer behavior. This effect is complex due to the interaction of variables such as SR-FNE and PP. These findings indicate that the effect of SIT_DC does not depend on a single variable but varies under different psychological and economic conditions. The results highlight that the perceived value of a recommendation and its social implications collectively influence C_Res, especially in areas sensitive to identity, such as fashion and personal care.

5.2 Theoretical Contributions

This dissertation contributes significantly to the literature on the effects of artificial intelligence (AI) and human-generated recommendations on consumer psychology by examining the interaction of social identity threat, stereotype related fear of negative evaluation, and price to explain consumers' responses to personalized recommendations. These contributions are explained in detail below:

1. The Role of Recommender Type in the Context of Social Identity Threat: Emerging a New Mediator

In the existing literature (Hertz and Wiese 2019; Castelo, Bos, and Lehmann 2019; Wien and Peluso 2021; Z. Li, Rau, and Huang 2020), preference differences between AI-R and H-RE have generally been explained in terms of task type (analytical vs. social), product type (hedonic vs. utilitarian), or perceived competence. However, this dissertation analyzes the recommender type to social identity threat and the consumer response path. It introduces social identity threat to the literature as a new mediator variable that has not been studied. Specifically, it reveals that AI-generated recommendations may provoke greater identity threat than human-generated recommendations, despite being perceived as more objective or data-driven.

This finding parallels the findings that recommender preferences change depending on the nature of the product, especially in studies such as Jin & Zhang (2023) and Longoni & Cian (2020). It opens a new theoretical window by modeling emotional and social reactions through perceived group affiliation threats. Also, this finding complements studies such as Gillespie et al. (2012) and Phillips-Brown et al. (2023), who argue that algorithmic neutrality is an illusion, and recommendations can carry social risks even when perceived as personalized. By modeling identity threat as a psychological mediator, this dissertation fills a theoretical gap regarding the social consequences of AI objectivity.

2. Modeling the Link between Stereotype Triggering and Fear and Identity Threat: Examining a New Moderator

Yalçın et al. (2022) and Srinivasan & Sarial-Abi (2021) have examined psychological reactions such as anger, perception of justice, or type of error while explaining why algorithms are sometimes perceived as less trustworthy or less human. However, in this dissertation, stereotype-related fear of negative evaluation (SR-FNE) is modeled as a significant moderator that increases the effect of SIT_DC. This work shows how cultural anxieties about being categorized or labeled in a certain way by algorithmic systems can heighten consumer vulnerability.

This finding is consistent with the lack of empathy explained through anthropomorphism in the study of S. Li, Pelluso, and Duan (2023). However, this dissertation deepens the explanation by emphasizing the internalized threat of social exclusion, linking it to identity performance in digital environments (Goffman 1959; H Tajfel and Turner 1986).

3. Visual Representations and the Threat of Dissociative Reference Groups

A novel experimental contribution is visual stimuli representing dissociative reference groups—something missing in prior studies, mainly using textual manipulations (J. Li et al. 2020). Based on the fundamental theories of White (2013;2006) and Berger & Heath (2007), the dissertation reveals that product imagery linked to dissociative reference groups dramatically raises identity threat, particularly when AI recommends it. This phenomenon can be understood as a datafication of identity concerns; when an AI system recommends a product associated with a dissociative group, consumers may perceive what it suggests as a "recorded" aspect of their digital identity, which may trigger defensive responses. This offers theoretical and methodological innovation, introducing image-based identity cues into the personalization literature.

4. Identity can override stylistic fit: Social identity threat as a stronger driver than aesthetic congruence

This research challenges the widely held assumption that stylistic or aesthetic fit between the consumer and the product leads to higher acceptance. Even when the product was visually congruent with participants' preferences, participants rejected it if it was associated with a dissociative group. This suggests that protecting social identity can override personal taste. The finding extends the literature on identity-signaling and product avoidance (J. Berger and Heath 2007) by illustrating that identity threat may dominate even when a product "looks like" it should fit the consumer's style.

5. The Moderating Role of Price Perception: Modeling Rational Choices Beyond Identity Threat

Zhu et al. (2023) discussed whether including precise numerical expressions in AI recommendations is effective according to the product type. Similarly, this dissertation considers price perception (high vs low PP) as a moderator variable in the conflicting dynamics between identity threat and rational consumer decisions, explaining why consumers sometimes accept the recommendation despite identity threat. This reflects dual-process theories (e.g., Kahneman 2011; Chaiken and Trope 1999), suggesting that rational evaluations (e.g., low price, high value) can override emotional concerns under certain conditions.

This contribution supports the finding of Xie et al. (2022) that “AI recommendations are more accepted if there is conscious need awareness.” It shows that even psychological pressures, such as identity threats, can be weakened in the face of value perception. Thus, this dissertation's finding provides a multi-level explanation by revealing that rational and emotional decision processes should be considered together.

6. Threat Triggered by Dissociative Reference Group Images: A New Type of Experimental Manipulation

Studies such as Li et al.(2020) have only presented the recommendations in textual form, neglecting the symbolic effect of visual representations. This dissertation experimentally demonstrates how dissociative reference group images trigger threat perception. This contribution provides an important methodological contribution to both social psychology and consumer behavior by revealing how consumer identity is damaged by rational product categories and visually associated symbolic associations.

7. Latent identity threats and implicit avoidance: Consumers react even in the absence of explicit cues.

The findings also demonstrate that consumers sometimes reject recommendations even in instances where the threat to their identity is not clearly visible. This suggests that implicit or culturally encoded associations could trigger a defensive response, pointing to the role of latent identity threats in digital context. This contributes to the literature on implicit social cognition and digital cue processing (Oyserman 2009; Aaker 2018), showing that digital environments can activate self-protective mechanisms even without negative or dissociative content.

8. Interdisciplinary Expansion on the Social Effects of Recommendation Systems Constructed with AI as a Recommender

The study has established an important bridge between the fields of marketing, social psychology, and artificial intelligence ethics by explaining the basic manipulation that starts with the type of recommender (AI vs. human) with a multi-layered model, such as social identity threat, fear of stereotyping, price perception, and C_Res. This interdisciplinary approach is one of the rare studies that analyzes consumer behavior with outcomes such as purchase intention or recommendation acceptance and with psychosocial variables such as self-image, social harmony, and intergroup distance.

9. Methodological and Conceptual Contributions to the Literature

This dissertation significantly contributes to the literature at both methodological and conceptual levels by using advanced statistical modeling to analyze the multi-layered relationships among consumer behavior, recommender type, identity theories, and digital systems.

In terms of Methodological Contributions, this dissertation uses advanced analysis models such as moderated mediation (i.e., PROCESS Model 18) and moderated moderation (i.e., PROCESS Model 37) to test multiple interactions among variables such as recommender type (AI vs. human), social identity threat (SIT_DC), collective self-esteem (CSE), stereotype-based fear of negative evaluation (SR-FNE), and perceived price (PP). The application of these models provides a methodological framework often lacking in the literature to more holistically understand consumer behavior's multi-level and contextual nature (A. F. Hayes 2013). In addition, the limitations of some psychometric tools used in the study in cultural contexts are also revealed. It has been observed that collective self-esteem (CSE) and fear of negative evaluation (FNE) scales do not always show the expected factor structure in the Turkish context. Various studies in Türkiye (Baysu 2007; Çoymak 2018; Arıkan 2017; Günsoy 2011; Keleş and Uçar 2025) have reported that the sub-dimensions of the CSE scale, such as "public self-esteem" and "membership esteem," exhibit low reliability and insufficient structural validity. In most studies, significant structure was obtained only in the "importance of identity" and "private collective self-esteem" sub-scales. Similarly, in this dissertation, some CSE items (e.g., reverse-coded items 11, 13, and 15) contained culturally difficult-to-understand expressions and were excluded from the analysis. In this context, attention was drawn to the validity problems experienced in the direct application of Western-based scales, and an important methodological awareness contribution was made to the literature on scale validity and cultural adaptation.

At a conceptual level, this study offers an original theoretical perspective addressing new forms of social identity threat in the digital age (e.g., algorithmic personalization, recommendation systems, and digital tagging). Traditional social identity measures are inadequate to capture such algorithmic threats. This suggests that social identity and collective self-concepts need to be redefined and measured in ways that are appropriate for interactions in digital environments. In this context, the study provides a theoretical contribution to the "AI-based stereotype threat" concept. It suggests that classical self-report measures may not measure the nuanced psychological responses of individuals to the ways algorithms categorize them. Therefore, the study identifies a theoretical imperative by arguing that more sensitive and culture-specific models should be developed to understand identity vulnerabilities in the digital age. In addition, this dissertation has conceptual parallels with the approach in the work of K. White and Argo (2007). In this experimental study, CSE was assessed through gender-based social identity, and participants were asked to respond to statements such as *"I am a worthy member of the social groups I belong to."* However, in this dissertation, it was observed that Turkish participants attributed low levels of meaning to similar statements (e.g., "I am a valued member of my gender/generation") and had difficulty identifying with these statements. This situation indicates that individuals in collectivist cultures construct their group identity differently and that identity-based scales developed in the West do not yield meaningful results in every context. Therefore, a strong conceptual contribution is made to the idea that cultural context should be addressed more sensitively in social identity measurements.

10. Personalization Paradox: Over-Personalization and the Risk of Identity Fixation

Personalization has long been celebrated in the literature for increasing customer engagement, satisfaction, and conversion(Abbas 2024; Q. Gao 2024; Yiran Zhang, Tan, and Lee 2024). AI-assisted personalization is widely considered efficient and effective, especially when combined with behavioral insights, pricing tactics, or content optimization (B. Gao et al. 2023; Hallikainen et al. 2022; Hardcastle, Lizette, and Brown 2025). However, recent research has begun to highlight psychological negatives such as discomfort, identity threat, and perceived intrusiveness (De Freitas et al. 2023; Mallek, Bawack, and Bonhoure 2024; McKee, Dahl, and Peltier 2023), suggesting that personalization may have undesirable emotional and cognitive consequences, especially among younger, identity-sensitive groups such as Generation Z. This dissertation supports and expands on this emerging critical perspective. Empirically, we show that identity threat can occur not despite high personalization but rather when recommendations are remarkably congruent with disjunctive reference groups or trigger stereotype-related fears. These findings align closely with Mallek et al. (2024), who found that identity threat undermines recommendation acceptance, and De Freitas et al. (2023), who identified anthropomorphic discomfort as a source of resistance. At the same time, the results challenge the generally optimistic tone of studies such as Gao & Liu (2022) or Ifekanandu et al. (2023), which emphasize the uniformly positive impact of personalization. By showing that perceived personalization can backfire depending on identity congruence, this study nuances the personalization literature and expands its boundary conditions by introducing an identity-sensitive lens.

11. Reconciling Partial Findings with Theoretical Expansion

Although some hypotheses proposed in this dissertation were only partially supported or failed to reach statistical significance at the aggregate level, these results should not be interpreted as theoretical shortcomings. On the contrary, they reflect the context-sensitive, multidimensional, and sometimes paradoxical nature of personalized recommendation systems, particularly when social identity and perceived autonomy are at stake.

Rather than viewing these outcomes as failures, this dissertation frames them as signals of the complex and layered dynamics by which consumers interact with AI-generated recommendations in digital shopping environments. These partial results reinforce the necessity to reconceptualize personalization models not as linear or universally effective systems but as dynamic, conditional, and psychologically moderated processes. By highlighting the influence of cultural norms, identity-based vulnerabilities, and individual-level psychological moderators, this study invites future research to develop adaptive personalization paradigms further. These paradigms should be designed to account for aesthetic or behavioral alignment and the social and emotional meanings embedded in the act of recommendation itself.

5.3 Managerial & Practical Implications

The results of this dissertation provide actionable insights for marketers, UX designers, and managers operating in the design and implementation of e-commerce and AI-based recommendation systems. The study reveals that recommendation systems should be evaluated not only by technical accuracy or user-interest-based content but also by recommendations' visual, linguistic, and social impacts. In particular, the finding that social identity threats can lead to negative perceptions and a decrease in purchasing behavior in specific user segments opens a new area of attention in marketing strategies.

First, today, many brands aim to improve consumer experience by using personalized visuals, reference groups, and product messages in recommendation systems. However, when designing these AI-RSs, it is necessary not only to limit users' browsing history and preferences, but also to consider the potential effects of social representations and social norms. Especially in the visual personalization process, presenting dissociative cues such as age, weight, and gender roles together with recommended products can negatively affect the positive relationship that users will establish with the product. For example, a young woman being recommended a product image featuring an older female model may unintentionally cause her to associate the product with old age. Similarly, low-income individuals encountering images that indicate high status may create an exclusionary or mocking perception. Such experiences may lead to a sense of social distance, a perception of threat, and avoidance of purchase in the consumer. In this context, an important insight for marketing experts is that style or aesthetic harmony alone is insufficient. In AI-based recommendation systems, group associations and social representations should be carefully analyzed to prevent the risk of users being identified with groups they do not want to belong to. Otherwise, the recommendations offered by the system may create reflexive avoidance behavior in the user and weaken the bond with the brand. Therefore, recommendation systems should be structured sensitively regarding technical accuracy and sociocultural meanings. Especially for identity-sensitive consumer groups, it is critical to prefer neutralized images and inclusive language and to make careful visual choices in categories open to stereotypes such as age, gender, and body type.

Second, partial support for the recommendation-type effect suggests that recommendations from H-RE have perceived trust advantages among certain demographic groups. Hybrid systems that allow users to choose or alternate between AI and human agents may improve engagement. Third, studies demonstrate the interactive effects of high price perception and social identity threat. Especially among individuals who are sensitive to social pressure, presenting identity-threatening images together with high prices can significantly increase perceived feelings of exclusion. For example, featuring an “idealized, thin-bodied” figure in a corset advertisement and simultaneously presenting the product at a high price can create a sense of “not belonging” in the consumer, both physically and economically. Such interaction weakens purchase intentions and can trigger distance and rejection behaviors in the user toward the brand. In this context, when the fear of negative evaluation (FNE) and PP are considered together, the adverse reactions to identity-threatening recommendations are further exacerbated. Therefore, it is of great importance for marketers to avoid presenting high prices together with socially sensitive images in targeted promotions. When targeting identity-sensitive users, context-sensitive personalization strategies need to be developed. These strategies include reorganizing the ad's tone, visuals, and pricing signals to suit the user profile. In particular, when visuals that include reference groups to which the person may not feel they belong should be used, the message language should be made more inclusive; promotions that appeal to price sensitivity and personalization messages based on user control (e.g., “Based on your previous purchase”, “Based on your favorites”) should be used to reduce the perception of threat.

Fourth, this research suggests that psychographic variables should be considered in addition to traditional demographic criteria (age, gender, income level) in consumer segmentation. Consumer segmentation emphasizes the importance of behavioral preferences and psychological and identity-related vulnerabilities. Integrating psychographic profiles (e.g., FNE scores) into recommendation algorithms can enable more responsible and effective personalization. It can detect threats even with the slightest social implications in recommendations. Therefore, developing algorithms to predict social sensitivity levels is important to learn from users' past reactions and system behaviors.

Finally, the development of AI-RS should be evaluated not only on technical accuracy or click-through rates but also on users' psychological well-being and social integrity. It is advisable to integrate feedback mechanisms that enable users to identify content as disruptive or socially incompatible, thus enhancing the system's context and subject based sensitivity.

5.4 Limitations and Future Research Directions

Despite this dissertation's considerable theoretical and practical contributions, several limitations exist that provide avenues for further research.

First, this dissertation used self-report scales such as social identity threat (SIT), fear of negative evaluation (FNE), and consumer reactions. Although such subjective assessments provide important information about the internal experiences of the participants, they may not fully reflect the actual behavioral responses. This may be because the participants avoided giving answers that were not socially acceptable, which made them feel vulnerable or insecure. In addition, in concepts related to social anxiety, such as FNE, the participants may have a strong tendency to idealize themselves (social desirability bias). In other words, instead of revealing the fear or anxiety they experienced, they may have preferred to give answers that were socially accepted or seen as “good.” The fact that the participants noticed the experimental manipulation (e.g., a clear understanding of the difference between AI-R and H-RE) may have also affected their natural responses. Thus, the effect of the manipulation may have been reduced or shifted in different directions. Therefore, physical or digital behavioral responses to manipulations (e.g., clicking, purchasing, avoidance behavior) could not be directly observed. In addition, participants' lack of motivation during the experiment, careless responses (straight-lining), or not taking the experiment seriously can be considered limitations of this dissertation in blurring the effect of psychological variables.

Future research could benefit from integrating behavioral data such as click-through rates, waiting time, shopping cart abandonment, or actual purchases to experimentally examine the extent to which identity threat triggers avoidance, delay, or compensatory behaviors in digital shopping environments. Future studies could build on this by developing multi-layered, segment-aware personalization models where the “voice” of the recommender dynamically adapts to the consumer's identity-related vulnerabilities.

The second limitation is ecological validity. Although the experimental design used controlled stimuli to isolate mechanisms such as recommender type or pricing cues, this necessarily limited ecological validity. In real-world applications, consumers are exposed to more complex recommendation environments, including algorithmic explanations and social proof elements (e.g., “people like you bought this”) in multi-layered recommendation systems (e.g., multiple products, user reviews, social proof, algorithm explanations).

Future research could simulate digital shopping environments where multiple products are listed, user reviews of these products are included, and explanations are provided as to why the algorithm made the recommendation, rather than simple scenarios where only a single product recommendation is presented. This would allow the impact of recommender type (human vs. AI) on social identity threat to be tested in more naturalistic contexts. Whether the recommendation comes from AI-R or H-RE, sharing other people's thoughts about that product during product evaluation is an important factor in product purchase or attitude. In addition, longitudinal studies can be conducted with Longitudinal Designs to examine whether consumers get used to these recommendation systems over time and whether recommendations initially perceived as a threat become normalized with repeated exposure.

A third limitation is that while this dissertation focuses on gender, socioeconomic status, and age stereotypes, other important identity dimensions such as political identity, religious affiliation, ethnicity, cultural values, or lifestyle remain outside the scope of the study. This does not fully reflect the diversity of social identity threats across different reference group contexts. Future studies could examine whether similar threats occur when political or religious symbols are recommended to consumers. They could also test whether the moderating and mediating mechanisms in these identity domains (e.g., price sensitivity, FNE) apply across intersecting identities or whether different dynamics emerge in culturally or politically charged recommendation environments.

The fourth limitation is the limitations of the SR-FNE scale. The Fear of Negative Evaluation (FNE) scale used in this dissertation was chosen to understand the level of social identity threat consumers experience through association with the recommended product and to test the effect of this threat on C_Ress as a moderator variable within the context of stereotype-related FNE. In the literature, the concepts of FNE and stereotype threat are closely related because when individuals worry that their social groups will be evaluated negatively, this may result in the experience of stereotype threat.

The FNE is a highly valid scale frequently used to measure social evaluation anxiety. However, the theoretical framework of this study goes beyond the traditional social anxiety context and focuses on the systemic and algorithmic stereotyping phenomenon that occurs in recommendation systems. In particular, the unique identity threats of the digital age, which cause individuals to feel “labeled” or “miscategorized” by being associated with an unwanted reference group through a recommended product, are addressed in this context. Therefore, the classical FNE scale used in the study may not have fully represented this more specific theoretical objective. In particular, the “perception of systemic stereotyping” at the center of the study—that is, the perception of a systemic logic behind the recommendations that positions individuals as belonging to an out-group—was not adequately captured by the FNE scale. In addition, participants may have had difficulty honestly reporting their social sensitivities. Admitting that the recommended content is discriminatory or stereotyping may be perceived as an embarrassing or politically sensitive issue by some participants. This situation can be interpreted as some items of the FNE scale, particularly not generating enough cultural resonance in the Turkish context.

This does not mean that the scale is completely inappropriate; On the contrary, it is close to the concept theoretically intended to be measured. However, more sensitive, contextualized, and digitally appropriate scales should be developed in this context.

Therefore, future studies should develop scales that measure psychosocial processes specific to digital contexts, such as algorithmic stereotyping, AI-based fear of labeling, and involuntary attribution of belonging to social groups. The current FNE scale can serve as a starting point in this context; however, it is suggested that this scale be adapted to the sample culture, the items be reframed, or a more specific conceptualization, such as "AI-based stereotype anxiety," be made. Moreover, new or refined scales should be developed to reliably assess social identity threats and self-conscious emotions in digital environments. Variables such as self-interpretation (independent or interdependent), public self-consciousness, or internalized stigma may provide more robust insights into the psychological moderators of personalization effects. In addition, exploratory studies supported by qualitative research will play a critical role in understanding the threat perception experienced by users in the face of recommendation systems to understand such psychosocial processes in more depth. Additionally, variables such as internalized stigma and public self-consciousness should also be tested in such models.

Fifth, this dissertation defined the recommender type only as AI or human. Today, recommender systems come in much more diverse and hybrid forms (e.g., avatar, chatbot, community-based recommender). This binary classification limits the variety of social meanings that users attribute to recommenders. Future studies should examine perceived authorship ("Who do users believe is behind the recommendation?") and investigate how anthropomorphic cues affect trust, threat, or resistance, especially when AI is designed to appear "human-like" (Waytz and Norton 2014, 434-44).

The sixth limitation is related to the collective self-esteem scale. In this dissertation, the Collective Self-Esteem (CSE) scale was used to understand the self-values of individuals arising from their group memberships. However, during the application process, it was observed that the participants had difficulty understanding some of the statements. This situation indicates the limited cultural compatibility of the scale in the Turkish context. Indeed, the concept of CSE has been studied intensively in Western-centered individualistic cultures and operates through the individual's sense of belonging to his/her social group and the self-evaluation he/she receives from the status of this group in society. However, in more collectivist cultural structures such as Türkiye, the individual's self-perception is shaped more by fulfilling social roles, ensuring group harmony, and community relations. Therefore, an individual's self-evaluation based on the "value of his/her group" may have lower explanatory power than in the Western context. This difference shows that self-perception is culturally structured differently and that single-type scales may be inadequate for measurements in this context.

Some CSE scale items also produced conceptual ambiguities even when translated into Turkish, leading to different interpretations of abstract concepts like group pride and social status. This circumstance limited the interpretability of the data and the validity of the theoretical model.

In the future, researchers should check the conceptual validity of the CSE again in countries like Türkiye. Alternatively, comparative studies should be conducted with scales such as the Rosenberg Self-Esteem (RSES), which more directly measure the individual's general self-esteem and are more widely used in the Turkish cultural context. In addition, developing new contextualized, culturally sensitive tools to measure individuals' relationships with their groups is critically important. In this context, measurement systems that integrate independent vs. dependent self-constructs, group cohesion, motivation, or cultural belonging may provide more robust internal validity.

As methodological limitations, although the experimental and statistical methods used in this dissertation have produced meaningful data in testing the relationships between recommender type and social identity threat, the fact that some hypotheses were only partially supported points to the multi-layered nature of these relationships. In particular, the fact that H1 was not supported in the general sample but showed significant differences in some demographic subgroups revealed that the effects of personalization are sensitive to context, product, and individual differences. This situation shows that personalization itself should also be personalized and that one-dimensional models may not be sufficient. Exploratory studies incorporating quantitative and qualitative methods to understand participants' internal reactions, motivations, and perceptions will significantly enhance future research. In order to understand how social identity threat creates a cognitive and emotional effect on individuals, methods such as in-depth interviews, content analysis on different social platforms (for example, collective discourse on the brand or product on platforms such as Ekşi Sözlük), and focus group studies are recommended. In addition, in order to better understand these complex psychosocial processes, multi-level and mixed models that include contextual factors such as personality traits, perception of product privacy, language of the recommender, level of social group affiliation, tone of the recommendation content, and visual presentation should be designed in future studies. Thus, the "type of recommender" and whether the recommender is perceived as "a friend or an external actor" can be tested. Although some of the hypotheses in this dissertation were only partially supported or remained at the statistical significance threshold, such results should not be interpreted as a weakness of the theoretical framework.

These results, on the other hand, reflect the context-dependent, multidimensional, and sometimes paradoxical nature of personalized recommendation systems, especially when it comes to social identity and perceived autonomy. By doing this, this dissertation revealed that it was necessary to come up with novel concepts by testing existing explanatory models. Thus, the findings of this study, which are complex and conditional, provide a rich and transformative foundation for future research rather than serving as a "conclusion" in the field.

Finally, regarding generalizability and cultural differences, collecting data only from participants living in Türkiye within the framework of non-probability sampling, with convenience sampling, may limit the generalizability of the findings. It is possible that certain groups were overrepresented in the sample due to factors such as the participants' digital literacy level, social media use, or academic background. In addition, sociocultural norms specific to Türkiye (e.g., age perception, body image, gender roles, class differences) may differ significantly from other cultures, thus limiting generalizability to other societies. Cross-cultural replications can test the generalizability of identity threat mechanisms. They should be conducted with multicultural samples to test how cultural dimensions such as individualism-collectivism or uncertainty avoidance shape responses to personalized recommendations. However, this also provides theoretical groundwork for studies in new cultural contexts.

In future studies, quota sampling or stratified random sampling methods should be used with larger and more representative samples (especially in categories such as age, gender, income, city, education, etc., to provide sufficient subgroup observations); thus, more precise comparative analyses should be possible. Because, again in this dissertation, the number of observations in some cells under demographic breakdowns such as gender, age, education, and income groups remained below 30. This situation made it difficult to make meaningful statistical comparisons and limited the in-depth interpretation of the findings at the subgroup level.

In conclusion, this dissertation has argued that personalized product recommendations may unintentionally trigger social identity threats; however, this has ultimately led to opportunities for further research in related areas. Refining theoretical models, increasing ecological realism, and adapting design and measurement practices to accurately reflect diverse psychological and cultural contexts are critical to contemporary consumer behavior literature. It is also essential to focus on refining, redeveloping, and validating consumer-focused identity threat scales specifically designed for digital personalization contexts. Such work will enable researchers and practitioners to develop effective, welfare-friendly, inclusive systems.

CONCLUSION

This dissertation explores the impact of personalized product recommendations, whether provided by human (sales representative) or AI (RS), on consumers' concerns regarding social identity, their cognitive assessments, and their emotional responses. While personalization is often regarded as a key component of consumer engagement (Abbas 2024) the findings of this study underscore its capacity to trigger social identity threats inadvertently. This is especially pertinent when products are associated with stigmatized or dissociative social reference groups, including those related to age, gender stereotypes, or low socioeconomic status (K. White and Dahl 2006; J. Berger and Heath 2007; Ukrainets and Homburg 2021).

Experimental studies have discovered that a product may be neglected by consumers, even if it aligns with their personal preferences or functional needs, if it represents a threat to their desired self-image or social identity. This effect was pronounced in categories linked to identities, such as products that challenge male masculinity or those targeted at individuals from low socioeconomic backgrounds. In these cases, the symbolic meanings associated with these items often overshadowed personal assessments of their importance or practicality. The results underscore the intricate relationship between cognitive evaluations, including aspects like product quality and value, and the social signaling processes that shape the messages a product conveys regarding an individual's identity.

This tension is exemplified by dual-process theories such as the Elaboration Likelihood Model (ELM) (Petty and Cacioppo 1986), which posits that individuals process information via both central (rational, deliberative) and peripheral (social, affective) routes. This dissertation demonstrates that these pathways often interact and can occasionally conflict, shaping consumer decisions intricately. In some cases, consumers might understand a product on a cognitive level through a central processing route, but they may still reject it due to its perceived social implications, which can be evaluated through a peripheral route. This underscores the considerable impact that worries regarding social conformity can exert, frequently overshadowing personal preferences.

Moreover, the study provides important insights into how dissociative concerns and SR-FNE operate as moderators within this intricate relationship. Individuals who are more aware of social judgment or possess a heightened inclination to distinguish themselves from outgroups demonstrate a greater sensitivity to personalization cues that they interpret as potentially threatening to their identity. Previous studies indicate that concerns related to dissociation and the fear of negative evaluation play a crucial role in contexts marked by social sensitivity and visibility. This includes factors such as body image, age, and consumption behaviors shaped by social class. The impact of these effects was notably heightened in scenarios such as vice-framed product recommendations, where the presence of AI prompted more pronounced adverse reactions (Wien and Peluso 2021; Yang et al. 2024).

This research highlights the complex relationship between the origin of the recommendations—whether they come from H-RE or AI-R—and the symbolic and identity-related dimensions that are inherent in those recommendations. Although AI can be seen as more objective, it frequently falls short in terms of perceived empathy, which can hinder its effectiveness in areas that are sensitive to identity or focused on pleasure (Longoni and Cian 2020; Castelo, Bos, and Lehmann 2019; Jin and Zhang 2023).In contexts prioritizing utility or task completion, AI often demonstrates superior competence and efficiency compared to humans, particularly when user requirements are clearly defined (Xie et al. 2022; Yueyan Zhang et al. 2025). Interestingly, the effects were not uniform; both human and AI recommenders yielded distinct psychological outcomes, which were further shaped by factors such as self-esteem levels, price sensitivity, and the context in which they were presented.

According to the results, personalization strategies should do more than just make predictions more accurate or better fit for every individual. It is essential for marketers, UX designers, and AI developers to thoughtfully reflect on the emotional significance of recommendation content (Wien and Peluso 2021; Sung et al. 2023), its links to identity, and the possible dissociative risks that may arise from both the product categories and the broader recommendation experience. How visuals, wording, and interface design are designed can significantly impact how consumers interpret a recommendation, determining whether it is perceived as complementary or intimidating.

This study provides important insights into the interaction among personalization and identity theory, stigma management, and impression formation in digital environments. Adopting an individualized viewpoint on consumer decision-making is crucial, acknowledging the complex interactions between internal psychological motivations and external social influences. It encourages organizations to develop recommendation systems that are both ethically conscious and psychologically secure, recognizing the complex nature of user identity and managing apparent oversimplified stereotypes.

This research broadens a range of intriguing opportunities for future investigation, including the potential for cross-cultural replications, improvements in behavioral measurement methods, and the development of more effective metrics for identity threat specifically designed for contexts involving AI. With an increasing number of personalized digital experiences, it is vital to comprehend and address their unintended psychological impacts. This consideration should be viewed as a research priority and a fundamental element of the design.

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APPENDICES

Appendix A. Result of the Evaluation by the Ethics Committee

Result of the Evaluation by the Ethics Committee is available in the printed version of this dissertation

Appendix B. Ekşi Sözlük Entries

<u>Disosiyatif Cinsiyet Stereotipi – Erkek Dudak Parlatıcı (Feminen)</u>

"aynı zamanda ayaklarına pedikür yaptıran bir ılıktır."

(kibariye canavari -02.12.2017 00:40)

"*alay konusu olan "erkek" bilinen erkektir...*

bunlardan bir tanesi bana "yikanirken yumusatici mi kullaniyorsun?" diye sorardi.. ilginc.".

(tubytube - 18.04.2012 10:44)

"*bunu bilen erkek dünya ahiret bacımızdır*."

(gelgelsarisinimsagyapgel - 11.10.2023 08:24).

"*götü ve başı ayrı oynuyordur."*

(sosyal reis- 11.10.2023 09:30)

"bu farkı bilen kadın sayısı bile azken erkeğin bilmesi şüphe uyandırıcı (*lipstick ile lip balm arasındaki farkı bilen erke*k*"*

(bajic - 11.10.2023 10:38)

".....lipstick, lipbalm ve lip gloss ayrımını bilen gayet de ılık erkektir. ha şu andan itibaren sözlük sağolsun ben de biliyorum. beni de ılıttınız "aq.

(spain - 11.10.2023 14:06)

"*aynı zamanda ayaklarına pedikür yaptıran bir ılıktır."*

(kibariye canavari - 02.12.2017 00:40)

"*erkek mi ? bunu bir daha düşünmek lazım derim."*

(gerut - 02.12.2017 12:31)

"*haftasonları halı saha maçı yerine bale yapar***."**

(kibariye canavari - 02.12.2017 16:34)

"*inceden ılıktır, kaygandır*."

(gavur dagi uzumu - 02.12.2017 20:09)

"*biraz şey bi erkektir."*

(dovletbizebokmir - 07.01.2022 19:58)

"kendisini güldüren erkeklerden hoşlanıyordur"

(kavimler gocunde evi yagmalanan adam- 07.01.2022 20:5)

"*iki kişi tanıdım bunu ortalık yerde, yanımda yapan. ikisinin de gay olduğuna yemin edebilirim, ama ispatlayamam*."

(mikro 33 - 07.01.2022 21:22)

"ılığın önde gidenidir"

(memoli1934-07.01.2022 23:15)

"*büyük ihtimalle gaydir***.".**

(lmrvnx - 08.01.2022 15:28)

"*kendisine çiçek alan erkeklerden hoşlanıyordur*."

(kavimler gocunde evi yagmalanan adam -15.11.2022 14:19)

"*biraz şeydir. ondan işte*"

(verandapera 15.11.2022 19:27)

"*oje süren erkeklerin kankası olan erkektir*"

(kavimler gocunde evi yagmalanan adam - 18.05.2023 14:09)

"*hafiften yumuşama başlamıştır*.

(yyildirayy - 02.12.2024 13:46)

"*toplum icinde tayt da giyer bu".*

(komutan bey - 18.02.2025 14:53)

<u>Asosiyatif Cinsiyet Stereotipi – Erkek Dudak Parlatıcı (Bakımlı)</u>

"*dudaklarının soğuk havalarda çatlamaması için önlem alan erkektir. kullanın, kullandırtın.sonuçta bu ruj değil.renksiz kokusuz olanları da mevcut. Ha ruj da olsa size ne*?"

(parlament mavisi - 02.12.2017 00:51 ~ 02.10.2018 15:49)

"*ne için kullanıldığı da önemli tabi. askerde erzincanın soğugunda kulağına vazelin, dudağına da nemlendirici sürmezsen soğuk ve ayazın etkisiyle dudaklar ve kulaklar çatlar yara olurdu. çarşı izninde eczaneden rengine bakmadan aldığım pembemsi lipsticki birkaç gün sürerek tugayda dolaşmışlığım vardır. neyseki itin biri kamuflajın cebinden çaldı da adımız çıkmadı tugayda. hey gidii..*"

(serengetili - 02.12.2017 01:08)

"öpeceği kadının bedenini de düşünen erkektir. tebrik ederim kendi adıma."

(Tamamgidiyorum - 14.02.2025 22:47)

"*tabii ki de taşımalıdır. ne kendisi acı çekmek, iki gülücüğünün bedeli olarak boydan boya dudak yarmak ister, ne de başkaları konuşan nevada çölü görmek ister*."

(whocaresya- 29.11.2016 09:33)

"olmazsa olmazım haline gelmiştir. dudaklarımın kurumaktan her hareketi acı ya dönüşen kış aylarında çantamdan çıkartmıyorum. özellikle loccitane %100 shea butter lip balm fav."

(nunuu - 29.11.2016 09:54)

"*bir çok erkek var bole. durakları kuruyorsa krem sürmesinden daha doğal ne var"*

(yabancikiz - 19.12.2019 16:4)

"*cilt veya dudak kuruluğu sağlık sorunu sonuçta. teknik olarak kullanmaması için bir sebep yok*."

(sophieninhayali - 27.11.2020 13:03)

"*bakımlıdır. dudakları parça parça olmuş halde dolaşsa daha mı iyidir efenim ?*"

(aut disce aut discede - 31.01.2011 01:31)

"*soğuktan dudakları hiç kanamamış kişilerin anlamadığı, normal bir erkektir*."

(metalik- 31.01.2011 02:00)

isvec'te neredeyse tum genc erkekler. hava soguksa ve kurak toprak gibi dudaklara sahip olmak yerine opulesi yumusacik dudaklar istiyorsan yaparsin. yoksa bir kurbagayla opusmeyi bekleyen kizlarla takilirsin.

(letranger - 19.12.2010 19:26 ~ 19:27

"*bunu yapan 99 erkek tanımıştım ben askerde.*

komutanların uyarısıyla poşet poşet dudak nemlendiricisi alınmıştı birliğe. içtimaya çıkmadan önce aynaya bakıp dudaklarını nemlendiren, nemlendirici tutan ellerine birazdan g3 alacak 100 tane vatan evladı. çok ironik ve çilekli bi görüntüydü allahım."

(izaleisuyuu - 19.12.2010 14:00)

"*ne metroseksüeldir ne de eşcinseldir. sadece ve sadece dudağı kuruyordur o kadar. hatta kimisi çantasında ellerine zaman zaman sürmek üzere krem bile taşır. (bkz: o benim) haaa konu erkeklik olursa onda entry yazmayla iddialı olunmuyo tabi. hele yanında lip stick taşımamayla hiç olunmuyo. taşırım abicim. beyin yerine başka bir organ taşımaktan çok daha iyidir*."

(yesilplastik - 19.12.2010 14:59)

"*dudak kuruluğu olabilir, illa trans mı olsun*"

(bahanesi olmayan adam - 02.12.2017 11:50 ~ 11:51)

"*bakımlı erkektir. kurumuş dökülen yüz derisiyle, kepekli saçlarla, yağ ve ter kokarak gezmez. temizdir. dudak nemlendiricisi kullanan erkek "ılık" değildir; ama hiç kullanmayan pasaklıdır, metrobüste yanına oturulmaz çünkü kokar, kişisel bakımdan bihaberdir.*

sonra da ona buna ılık diyip "bu garılar niye bana bagmıyorlar yav" diyorsunuz. mağaranızdan çıkmayı deneyin. kokuyorsunuz."

(kutsaljartiyer - 02.12.2017 12:02 ~ 12:06)

"*dudak nemlendiricisi kullanmak neden bir cinsiyete özgü hali getirildi merak ettim*"

(birgaripabukat - 03.12.2017 00:07)

"*soğuk havada dudakları çatlayan erkektir. (bkz: el kremi kullanan erkek*)"

(burnteam - 07.01.2022 23:38)

"*çok normal bir durumdur*"

(gevrek diyen izmirli - 08.01.2022 00:28)

"*gayet normal bir erkektir. kupkuru pis görünen dudaklarla mı gezsinler. bence sürün aferin*".

(**miss illyrian - 08.11.2022 16:47 ~ 16:57)**

"*Erkeklikten bir şey mi eksiltiyormuş?"*

(utopikdusunceler - 15.11.2022 15:24)

"*insanız, bizim de dudağımız çatlıyor."*

(nickimdeboncukvar - 15.11.2022 15:25)

"*kendine bakan erkektir, tek bir kere görülse bile akılda kalır.*

(couronne boreale - 15.11.2022 16:40)

"*normal erkektir.belde silah,elde araba anahtarı gezen kekolardan iyidir*."

(humuslupilav - 15.11.2022 18:45)

"*kesinlikle normal olup garip hiç bir tarafı yoktur.kadin veya erkek olsun her dudak çatlar ve önlem olarak nemlendirici veya benzer bir şey ile önlem alınmalıdır*."

(vajina terbiyecisi - 15.11.2022 19:03)

"*gayet normal erkektir. hatta artırıyorum ankara gibi bir şehirde yaşıyorsa dudak nemlendiricisi kullanmaması anormal karşılanmalıdır*."

(godblessankara - 15.11.2022 20:31)

Disosiyatif Yaş Stereotipi – Erkek Kasket (yaşlı ve köylü)

"*aynı zamanda minibüsçü şapkası"*

(atina fisildayan yazilimci - 13.11.2013 17:58)

"*takmak için asgari 40 yaşında olunması gereken başlık. yaşlanayım diye bekliyorum*."

(espera - 16.01.2012 05:32)

"*dede şapkası*".

(olmuyorsakicelim)

"*akdeniz bölgesinde yaşlıların giydiği şapka*."

(fur1907kan -22.10.2022 18:32)

*"koylu amcalar ve asker emeklisi amcalar tarafindan cok tercih edilen sapka cesididir. (hos gunumuzde bu kasketin yerini her nedense takkeler tukkeler almaya basladi ama) koylu amcalar tarafindan gayet basit, siradan olani ve genelde grisi tercih edilirken, emekli asker amcalar tarafindan delikli (hasir gibi) ve acik renk olanlari tercih edilmektedir. ayrica koylu amcalar tarafindan bu sapkaya namaz kilimi esnasinda 180 derece dondurmek suretiyle siperligi arkaya gelecek sekilde hemen transform*edilebilme ozelligi kazandirilmistir.*

kangol firmamizin urettigi versiyonlari da gerek alamanci, gerek clubber genclerimiz ve kodaman amcalarimiz tarafindan (bilgi yani emek yanindan agir basan serbest meslek erbabi; ki bunlar avukat, müsavir vs.dir.) kullanilmaktadir.

uluslararasi bir vizyondan baktigimizda ise bunlarin kirmizi ve yesil tonlarinin agir bastigi ekose desenli olanlarini irlandali amcalarin kafasinda rahatlikla gorebiliriz."

(Zaknafein - 04.08.2005 10:02)

"ötede beride , yaşlı amcalarda görüldüğünde nostalji hissi uyandıran başlık."

anadolu felsefesi-05.11.2007 10:49

"dede şapkası."

Olmuyorsakicelim-14.11.2019 01:08

“ileride kendime 35. yaş günü hediyesi olarak alacağım tekstil ürünü.

kirli sakal ve güzel bir atkı ile kişiye olgun bir görünüm katar.”

(alwaysbetter-16.11.2018 01:57)

“dedemin, uyumadan önceki her anında, yemek yerken, çay içerken, gezerken kısacası aktif olduğu her zaman başında bulundurduğu başlık.”

asiiigenc-02.09.2020 23:56

“kafamdayken ziraat bankası'na ne zaman girsem, tam olarak o ana ve o mekana ait hissetmemi sağlayan başlık, serpuş, aksesuar..”

“hani harmanı kaldırmışım da parayı şubeye yatırmaya gelmişim sanki..”

sahlanankoc-15.03.2021 10:06

“aynı zamanda minibüsçü şapkası”

atina fisildayan yazilimci-13.11.2013 17:58

<u>Asosiyatif Yaş Stereotipi – Erkek Kasket (tarz sahibi)</u>

"*Tesadüf müdür bilinmez, ülkeimzde en çok tevazü sahibi ve halktan biri olarak tanınan liderlerle özdeşleşmiştir. en çok süleyman seba'ya ve bülent ecevit'e yakışmıştır herhalde.*

http://image.cdn.haber7.com/...520110410094924601.jpg

http://www.medyatava.com/…-nin-hikayesi-379-247.jpg"

(en iyi altinci adam14.08.2014 17:2)

"*ben bunları çok seviyorum. dedem takardı koyu renk kasketler. bir de eski filmlerde genç erkekler takıyordu. çok hoş doğrusu. birkaç yıl önce kasket sevdam tutunca kendim için aradım, ama bulmak ne mümkün. sonra bir moda oldu. neredeyse her mağazada peydahlandı. ortalık kasketten geçilmiyor. aldım kendime kırmızı bir tane. ara sıra takıyorum. cidden çok tatlı bir şey bu kasket. tam aradığım tarzda (piyasadakilerin çoğunu sevemiyorum) çizgili bir şey bulsam alacağım bir tane daha."*

(missspi - 17.09.2018 21:07 ~ 21:08)

"gayet hoşuma giderek taktığım şapka çeşidi."(bkz: flat cap)

(hanim nickimi getir - 05.11.2018 19:43)

(bkz: yakışıklı bekar genç ve atom mühendisi erkek)

(ben de bir gun yazar olurum belki-01.08.2009 22:51)

<u>Disosiyatif Yaş Stereotipi – Kadın Pijama (Menopoz)</u>

"*Sabır gerektiren dönemdir . o da geçiyor rahat olun*"

(hircinli - 08.01.2008 04:34)

anneler girince bir an önce çıkması için dua edilen dönem..

miyuw-11.02.2003 00:19

devlet dairelerinde çalışan çoğu kadının içinde bulunduğu durum.en azından ben öyle düşünüyorum ve bu durumda olanlara kafa atmak istiyorum.*

ego maymunu-03.12.2004 23:37

bazi biyologlara gore evrimsel bir adaptasyondur. bu fikre gore, menopoz goren atalarimiz, belli bir yastan itibaren seks, hamilelik ve cocuk dogumunun sayisiz risklerinden korunduklari gibi, enerjilerini es bulmak ve yeni cocuklar yetistirmek yerine torunlarini yetistirip buyutmek icin kullanmislardir, ve dolayisiyla kendi genlerini ilerki nesillere aktarmada menopoz gormeyenlere gore daha basarili olmuslardir. bu yuzden de nesiller gectikce ortalik menopoz goren kadinlarla dolmustur.

muhendis-09.05.2007 21:14 ~ 21:15

eşcinselliğini saklayan, kadınlarla paravan ilişki komikliğine giren ünlü adamlar gibi, kadın ünlüler arasında da bunu saklama olayı var nedense. olm gelmişsin 50 yaşına, hala çocuk sorusu sorulduğunda "kısmet demek lazım, olabilir belki, bakalım" filan demiyor mu karılar, "nah olur abla, bu saatten sonra çocuk mu tutar o rahimde" diye çirkinleşesim geliyor. ne bu ya, ayıp bir şey mi yani menopoz,"artık geç kaldım tabii" de geç git çok ayrıntıya girmek istiyorsan o bile yeter ama hala ben doğurganım palavrasıyla gençlik mi ispatınızdasınız anlamıyorum ki.

red g-11.12.2010 15:35

müdürlerden uzak durası bir hadisedir. kadın zaten balkaymaktı anasını satiyim bi menopozu eksikti, tam oldu yani..

ne hormonmuş arkadaş neymiş bu kadar işlevli, ben salgılıyorum da noluyor mutluluktan bulutlarda mı geziyorum da bunda bitince bi haller geldi kadına bi tripler bi surat bi bilem ne.. al benimkini al yumurta mı istiyon ne istiyosan, yeter ki bi git yaa..

crystal defect-10.01.2011 09:21

hitabet olarak insana ne diyeceğini şaşırtan durum: abla mı diyek, hanım mı diyek, mahmut mu diyek, ne diyek?

non descript-07.11.2012 20:58

anneniz, teyzeniz, ananeniz neyse bi derece de aynı ofisi paylaştığınız kadının menopoz semptomlarını göstermesi hiç iyi bişey değil. gelgitli ruh hali, sürekli herşeyden şikayet edişi, hiç bir şeyden memnun olmayışı ve sürekli ortalığı karıştırmak gibi davranışlar sergilemesi sizin de "ben de yol yakınken gireyim de aynı anda çıkarız" demenize sebebiyet verebilir.

na undd-23.05.2012 14:03

hitabet olarak insana ne diyeceğini şaşırtan durum: abla mı diyek, hanım mı diyek, mahmut mu diyek, ne diyek?

non descript-07.11.2012 20:58

(bkz: menopoz teyze)

Gyne-07.11.2012 21:38

kadın yaşamının her evresinde olduğu gibi bin türlü saygısızlığa ve aşağılamaya maruz kalan son evredir.

Namedesanderen-24.11.2012 00:48

annemin evde cıngar çıkarma sebebi.

son 2 haftadır heyheyleri tepesinde. ve nasıl idare edeceğimizi bilmiyoruz. (bkz: hayat çok zor)

na undd-17.06.2015 11:56

hiç gelmesini istemediğim karanlık dönem. ağrım sancım da olmuyor. yetmiş yaşıma kadar adetlerim yerini bulsun isterim. bu konuda isviçreli bilim insanlarının yapabilecegi bi şey olmalı.

nihill snafu-26.01.2022 14:54

bilinçaltında kadınların artık değersizleştiğini hissettikleri durum.

çocuk veremiyorsam bittim. damn

ruzgarsevenadam-26.01.2022 15:00

her iş yerinde bir tane bulunur, ortalığın anasını s.ker bırakır.

Arttrade-02.07.2024 17:13

çalıştığım hastanede bir zamanlar menopoz polikliniği vardı. sadece menopoz teyzelerin geldiği bir poliklinik. günde 40-50 menopoz teyzenin geldiği bir poliklinik. çömez asistandım o zamanlar. bazı menopoz teyzeler insanın yaşam enerjisini tüketecek potansiyele sahiptiler. sürekli konuşan, konuşan, konuşan, hayat hikayesini anlatan, kendilerince terapi yapan, sıkıntıları hiç bitmeyen teyzeler. aklıma gelince beni de ateş bastı şimdi.

Gyne-02.04.2011 17:02

Asoiyatif Yaş Stereotipi Kadın Pijama (Pamuklu Pijama)

"*sözlükte sayıları oldukça fazla olan sıradışı ve etkileyici kadınlardır, auralarıyla etkilerler erkekleri. güçlü ve oldukça çekicidir bu kadınlar*."

not: 195 cm!!! boyunda z kuşağı

(kingkrule - 27.08.2024 12:31)

"*en asil duyguların insanıdır*."

(boun - 29.07.2010 17:30)

adet sancisindan muzdarip bayanlarin her ay belli donemlerde girmek icin can attiklari olgu.

Poison

yurt dışında bu dönemi yaşayan kadınların yüceldiği dönem

(mcneese-21.03.2004 16:57)

kadının doğurganlığının bittiği ve özgürleştiği döneme verilen ad.

bilinenlerin tümü safsata...

öğrenilmiş çaresizlikle menapoza giren kadın, öğrendiklerini yaşayabilir...

hayatı bilen kadın daha canlı, daha seksi, daha üretken, daha olgun, daha bilge yoluna devam eder.....

(isuva-29.07.2021 17:00)

kanımca bir hatun kişinin içinde en şirin durduğu, en gel sev beni diyen elbise türü. hele azıcık da uykulu duruyosa hakkaten tam anlamıyla yeme de yanında yat

(murdock-11.04.2003 22:01)

uğruna çılgın partiler düzenlenebilen tek kıyafet..

(Josephine-26.11.2004 01:57 ~ 01:57)

giyildikçe penyesi daha da yumuşayan, sıcacık olan, bir müddet sonra vücudun bir parçası gibi hissedilen huzur verici kıyafet. çıkartılıp yerine kot pantalon giyilirken o *pantalon çok yapmacık, itici, soğuk görünür insana, pijamasını bırakmak istemez. çünkü bir insanın içinde en güzel görüldüğü elbisedir pijama. yalan söylemez. böylesine bir sıcaklık, bir doğallık..*

(sir gawain-26.11.2004 02:02)

uyku kıyafeti.

pazar günlerinin vazgeçilmezi.

kabuslarla savaşırken ki üniforma, rüyaların piknik kıyafeti.

milyonlarca farklı deseni, rengi ve dokusu ile apayrı bir dünya.

kimisi yeşildir payetler olur üzerinde, kahverengi saten ya da, kimisi mor olur üzerinde minik bebek ayakkabıları vardır. bazıları minik tavşanlar, bazıları dev çiçeklerle bezelidir. en güzel aksesuarları dağılmış saçları tutturan toka, minik bir ayıcık uyurken sarılmak için ve uykulu gözlerdir.

pijamasız uyku hayal edilemezdir.

(janis baby-08.02.2009 22:42)

kesinlikler pamuklu olanı makbul yatak kıyafeti.

bir zamanlar böyle saten çeşitleri vardı, hayatımıza renk katacak gibi algılayıp aldık iyisini de kötüsünü de sonra anladık ki beden döndüğünde pijama dönmeyi rededіyor, hemen çöpe gitti.

sonra takım pijamalar geldi ki hayatım boyunca sevmedim bu tarzı sonra bir gün bir yerde denk geldi pazen denen hafif kumaştan yapılan önden düğmeli baba pijaması hatta babamla aldık uzun yıllar takım olarak giydik ki hala giyerim.

daha sonra pazar zamanları başladı ve ihracattan kurtulan şirin pijama altları geldi ve vayyy dedik elin ecnebileri ne güzel giyiniyor gece yatarken hem de takım olmak zorunda değil diyerek bakış açısı üstte atlet altta çizgili, kareli, desenli altlar olarak değişti.

hala tam takım pijama sevmem ama şu kyo veya la senza tipi yerlere bakınca kafama göre bir şeyler bulunuyor.

önemli olan tam pamuklu bir kumaştan olması ve kışın sıcak yazın ise, yazın pijama mı giyilir be.

(Kuturkuturyesilpapazerik-22.01.2014 20:29)

eve geldiğin an yatağının üzerinde "giy beni" diye gülümseyen yegâne dost, uyku arkadaşı..

(alyu-15.12.2016 13:33)

<u>Disosiyatif Cinsiyet Stereotipi – Kadın Korse (Büyük beden)</u>

"*hele bi de tayt giymişse tadından yenmez*."

(semsipasapasajindakiateist - 11.02.2013 12:49)

"*vardır böyle bir iticilik. kilolu bir bayan(veya erkek) gördüğümde eğer sağlık problemi yoksa iradesiz biri olduğunu düşünürüm. yemek yeme konusunda bile kendini kısıtlayamadığı için böyle düşünürüm elbette. bir de şunu anlayamam kilolu kadınlarda, kıyafet olabildiğince güzel, makyaj tam gaz, saçlar fönlü ama kilo 90, neye yaradı? kilonu kontrol edebilseydin de saçını toka yerine kalem ile toplasaydın bin kat iyiydi*."

(creeping dutchman - 02.12.2015 22:45)

"*iki yürüdü mü leş gibi terleyeceği için oluşan iticilik. az yiyin kızlar*."

(psychiatry - 02.12.2015 23:07)

"bunu kendi vücuduna özen göstermeyen kadının iticiliği olarak değiştirmek daha doğru bir yaklaşım olacaktır, zira kilo olarak ağır gelen bir kadın yüksek kas ve düşük yağ oranı sayesinde süper bir fiziğe de sahip olabilir. ama göbeğinden ve kalçalarından lömbür lömbür yağlar sallanan bir kadın hala börekleri pastaları gömüyorsa, iki egzersiz yapmaya da üşeniyorsa bakın işte o iticidir."

(Lstr80 - 07.12.2015 00:23)

"*vücuttaki alkole bakar. ayık kafayla itici gelen güzel kafayla çekici gelmeye başlayabilir.*

sabah uyandığında ben ne yaptım, neden bu kadar içiyorum, bununda bi haysiyeti vardı artık o da kalmadı... gibi düşüncelere sararsın."

(Anglosakson - 07.12.2015 13:19)

"*yaşı genç olupta pelikan yutağı gibi gıdısı olanlar, benden kalın bacağı olanlar, yiyip yiyip sıçmadığı halde hala yemeye devam edenler cidden aşırı mide bulandırıcı*"

(megawolt - 07.12.2015 18:28)

"*Tombiş tombiş ben almam. kadın dediğin kendine bakacak. tedavi ve ilaçlarla gelen kilolar dışında kadınların kilo alması saçmalık*."

(nebicimama - 08.12.2015 01:44)

"*bide cok yakisiomus gibi tayt giymiolar mi abi ıyyyyy tiksinç????"*

(Ddmhnc - 08.12.2015 13:14)

"*sağlığına dikkat etmeyen, evrimsel açıdan zayıf, kötü kodlara sahip insan iticiliğidir."*

(ruwenzori 3 - 10.12.2015 17:32)

"*kilolu insan iticidir. dünyanın hiçbir gücü kilolu bir erkeği yakışıklı ya da kilolu bir kadını güzel bulmamı sağlayamaz. kabul edin artık şunu."*

(burnuna sinek konmus somali katibi - 17.06.2016 17:38)

"*kesinlikle katıldığım tespit. hele birde 90 kilo ile avmlerde öküz gibi yemek yemeleri yokmu :("*

(azromania - 24.09.2016 07:34)

"*yazın çok kötü ter kokar iiiii*"

(uzunasikoglu - 07.01.2017 23:25)

"*durumu kendisinin seçmiş olmayışı, itici olduğu gerçeğini değiştirmez. ha seveni vardır, bize ne, allah bağışlasın*."

(leonfestinger - 08.01.2017 00:45)

"*kilolu insan iticiliği, kadını da erkeği de, insan dediğin kilolu olmayacak arkadaşım, net.*"

(without Wings - 08.01.2017 00:46)

"*böyle yanları fırlamış kadınlar oluo bide daracık giyinip çıkıyorlar vallahi kusmak geliyor içimden. hayır nasıl bir öz güven ben anlayamıyorum*."

(santiyecity - 08.01.2017 01:16)

"*hepsi de kesin kortizon tedavisi görmüştür. hiçbiri de hayvan gibi yiyorum demez*"

(bakanlarkurulu - 08.01.2017 01:31)

"*hiç sevimli ve şirin değiller kadın dediğin ince olur*"

(kraft71 - 08.01.2017 08:42)

“*Kendi kilo fazlama bakmam ama kilolu kızla sevgili olmam fakat (bkz: kanka gibi kanka)”*

(orijinalgrisapka - 08.01.2017 10:09)

“*kim ne derse desin var böyle birşey. domuz gibi kadınlar sevilirmi aq”*

(azromania - 11.03.2017 00:24)

“*bu iticilikten kurtulmanın herkesin bildiği bir yolu var. kilolu kadına bakmamak. bakmayınca görmüyorsun ve itici olmuyor. çok basit. denemenizi öneririm*.”

(you are my lethe - 11.03.2017 00:34)

“*hiç bir yemek zayıflıktan daha lezzetli değildir, deyip katıldığım durum*.”

(supurgesine park yeri arayan cadi - 11.03.2017 21:12)

“*entry bence kilolu kadın + tayt iticiliği yapılması gerekiyor!”*

(umco - 11.03.2017 22:10)

“*Göz zevkini bozmasının yanında karşı cinsten geçici bir soğumaya neden olan iticiliktir. bir de bu cinsin kendini güzel sanan versiyonları var ki insan gerçekten hayret ediyor bu özgüvenin sebebini*.”

(Six oclock - 14.06.2017 23:18 ~ 23:19)

“*sözlükteki kiloluları ortaya çıkaran başlık.kilolu degil ama obezlere uyuz oluyorum bencil ve andaval olduklarını düşünüyorum*”

(diyyepe - 18.06.2018 11:20)

“*asla katılmadığım başlık. aksine (bkz: kilolu kadın çekiciliği*)”

(constructive- 18.06.2018 13:49)

“olmayan iticiliktir. aksine çekicidir. tabi bunu herkes anlayamaz”.

(johnny adam - 17.05.2021 21:51)

<u>Asosiyatif Cinsiyet Stereotipi – Kadın Korse (Toparlayıcı)</u>

"*kiloludan kastınız ne kadar bilmiyorum ama balık etli bir kadın, 40 kilo civarı her kadından(evet bunlara da kadın deniyo) çekicidir gözümde. o ne lan öyle 40 kilo ile ben chest press yapsam göğsüm kasılmaz*"

(sizelain g - 11.02.2013 11:11)

"*is geregi kendileriyle biraz fazla zaman gecirince anlarsiniz ki kilolu kadin iticiligi degil, bariz bir cekiciligi var. gecen aramizda konustuk arkadaslarla, bir bana mi boyle geliyor diye sordum, meger hepimiz ayni fikirdeymisiz.*

kesinlikle uzak durulması gereken mahlukatlar amk, bir insanın vücuduna gösterdiği saygı kendine gösterdiği saygıdır, vücut formunu korumak için gösterdiği irade kişiliğini yansıtır."

(sfenkslee - 19.03.2014 06:25)

"*bıngıl bıngıl keşkül titretmeli yağlar amk düşündükçe kusacam. görünce hemen kaçın*

*not: bu entry boy kilo arasındaki fark 14-15 in altında olanlar içindir. **"

(dontgetanybigideas - 12.02.2013 07:47)

"*çağla şikel'in nasıl olduysa çok çok doğru bir şey söylediğine şahit oldum geçenlerde, programa telefonla bağlanıp karısının görüntüsünden şikayet eden bir adama cevap verirken: "sen bana bakma kardeşim, sen bana ne bakıyorsun. görüyorsunuz televizyonda mankenleri sonra yanınızdakini beğenmiyorsunuz."*

o insanlar hem öyle zayıf, hem sağlıklı, hem güzel kalabilmek için binlerce lira harcıyorlar. spor yapıyorlar, dengeli besleniyorlar. sadece tarhana, bulgur pilavıyla 36 beden kalırsan bir süre sonra hasta olursun. düzenli balık, kırmızı-beyaz et, fındık, badem, ceviz, zeytin yağı, tropikal meyveler vs vs vs yemezsen, düzenli vitamin almazsan, haftada en az üç gün spor yapmazsan olmaz o iş. karşıdan şoşmon kodon otocoloğo demek kolay. hasta etmeyin kadınları, bırakın yanınızda olmak istediği gibi mutlu kadınlar olsun, yazıktır la."

(shakespeareinsoytarisi - 07.12.2015 12:38)

“*yani balık etiyse gayet çekicidir, kadının hasıdır*.”

(messihan - 07.12.2015 14:53)

“güzel ve iyi bir kadın şişko olsa da güzel ve iyidir, çirkin ve lanet bir kadın zayıfsa da çirkin ve lanettir. aynı şeyler erkekler içinde geçerlidir. sonuçta herkes yaşlanıp fiziki özelliklerini kaybediyor.”

(kalyoda-08.12.2015 12:13)

“*çok cici olur lan bunlar yanılıyorsunuz*.”

(gkb - 10.12.2015 17:38

“*itici olmamakla birlikte, bazıları aşırı tatlı oluyorlar*.”

(bizdedevar- -10.12.2015 17:41

“*şişman kadınların daha mutlu ve güleryüzlü olduğu gerçeğini unutmayalım bence*

tanım: kilolu kadınların itici olduğunu düşünenlerin yazdığı başlık.”

(business intelligence specialist- 10.12.2015 18:49 ~ 27.04.2018 06:56)

“*kesinlikle katılmadığım olgudur yok öyle birşey efendim ne demek itici hiç de değil yani aksine pamuş ve tatlıdırlar*”

(sadeceodun - 12.12.2015 11:05)

“*yoktur. kütle büyür, çekim artar*.”

(zaphod beeblerox - 23.09.2016 18:44)

“*tersine, fazlasıyla neşeli ve sevimlidirler*.”

(liebknecht - 08.01.2017 00:03)

“*ben kesinlikle katılmıyorum bu fikre. kadın kadındır, kadın her haliyle güzeldir. huyu güzelse gerisi teferruattır*.”

(redmoon84 - 08.01.2017 01:24)

“*değnek gibi kadından iyidir. en azından kemik yalamazsın ve bir yerlerine bir şeyler batmaz*.”

(blackbad - 08.01.2017 01:41)

"*katılmadığım durum.*

kilolu olup çok tatlı ve şirin olan çok insan var. hatta ne diyeyim kilolu insanlar bana daha bir anaç ve samimi geliyor. kesinlikle iticilik bu insanlara yakışmayan bir kelime, herkes 36 beden olmak zorunda değil ne de olsa."

(bargeluna - 08.01.2017 12:45)

"*zayıf ve sıska bir kadından herzaman iyidir*"

(manofdifficult - 11.03.2017 10:36)

"*vurdunmu ses gelicek kilolo kadın candır yanlış başlık*."

(lawac - 11.03.2017 20:49)

"*itici mi. bence tam tersi*"

(amerikyumun simgesi-10.10.2017 04:00)

"*kadın dediğin hafif balıketli olacak zayıf çıtkırıldım olmayacak*".

(anatolianpars - 10.10.2017 11:34)

Appendix C. Measurement Items

	Measurement Items	Source
Collective Self-esteem scale	I am a worthy member of the social groups I belong to. I often regret that I belong to some of the social groups I do. Overall, my social groups are considered good by others. Overall, my group memberships have very little to do with how I feel about myself. I feel I don't have much to offer to the social groups I belong to. In general, I'm glad to be a member of the social groups I belong to. Most people consider my social groups, on average, to be more ineffective than other social groups. The social groups I belong to are an important reflection of who I am. I am a cooperative participant in the social groups I belong to. Overall, I often feel that the social groups of which I am a member are not worthwhile. In general, others respect the social groups that I am a member of. The social groups I belong to are unimportant to my sense of what kind of person I am. I often feel I'm a useless member of my social groups. I feel good about the social groups I belong to. In general, others think that the social groups I am a member of are unworthy. In general, belonging to social groups is an important part of my self-image.	(Luhtanen and Crocker 1992)
Social identity threat	The fact that my friend saw me with this product undermined my identity. My personality was challenged when my friends saw me buying this product The fact that my friend saw me buying this product threatened the way I feel about myself	Adopted from Ukrainets and Homburg (2021) developed from Steele, Spencer, and Aronson (2002) (K. White and Argo 2007)
Fear of Negative Evaluation	I worry about what other people will think of me even when I know it doesn't make any difference. I am unconcerned even if I know people are forming an unfavorable impression of me. I rarely worry about what kind of impression I am making on someone. I am afraid others will not approve of me. I am afraid that people will find fault with me. Other people's opinions of me do not bother me When I am talking to someone, I worry about what they may be thinking about me. I am usually worried about what kind of impression I make If I know someone is judging me, it has little effect on me. Sometimes I think I am too concerned with what other people think of me.	Leary (1983)
Overall Attitude towards recommendation	What is your general opinion of this personalized recommendation What is your general feeling of this personalized recommendation To what extent do you think you will accept the recommendation	Adapted from Whan Park et al. (2010)
	I would avoid buying the recommended product, I would ignore future recommendations from this source.	Elliott & Devine (1994).

	Measurement Items	Source
Attitudes towards the recommended product	Bad/good Negative /Positive Liked /Disliked	Wien and Peluso (2021) adapted from MacKenzie and Lutz,1989)
Dissociative concern	I dislike the associations of this product. I want to avoid being associated with this product. This product reflects who I do not want to be.	White and Dahl, 2006
Perceived Value	This product is a: (very good value for the money to very poor value for the money) At the price shown the product is: (very economical to very uneconomical) The product is a good buy (strongly agree to strongly disagree) The price shown for the product is: (very acceptable to very unacceptable) This product appears to be a bargain (strongly agree to strongly disagree)	Dodds, Monroe, and Grewal (Dodds, Monroe, and Grewal 1991)

Appendix D. A Comparison of Survey Questionnaire Items Between the Dissertation and the Source

Collective Self-Esteem- Luhtanen, R., & Crocker, J. (1992)	Kolektif benlik saygısı-Arıkan (Arıkan 2017)	Revisited by the author
-I am a worth member of the social groups I belong to.	Ait olduğum sosyal grupların değerli bir üyesiyim.	Ait olduğum sosyal grubun değerli bir üyesiyim.
-Feel I don't have much to offer to the social groups I belong to.	Ait olduğum sosyal gruplara çok bir şey sunmadığımı hissederim.	Ait olduğum sosyal gruba fazla bir katkım olmadığını hissederim
-I am a cooperative participant in the social groups I belong to.	Üyesi olduğum sosyal gruplarda katılımcıyımdır.	Ait olduğum sosyal grubumda iş birliği içinde hareket ederim
-I often feel I'm a useless member of my social groups.	Çoğu zaman sosyal gruplarımda faydasız olduğumu hissederim.	Çoğu zaman sosyal grubumda faydasız olduğumu hissederim.
-I often regret that I belong to some of the social groups I do.	İçinde olmak istediğim bazı sosyal gruplara üye olduğum için çoğu zaman pişmanım.	İçinde bulunduğum sosyal gruba dahil olduğum için zaman zaman pişmanlık duyuyorum.
-In general, I'm glad to be a member of the social groups I belong to.	İçinde olmak istediğim sosyal grupların üyesi olduğum için genellikle memnunum.	Genel olarak, ait olduğum sosyal grupta olmaktan memnunum.
-Overall, I often feel that the social groups of which I am a member are not worthwhile.	Genel anlamda üyesi olduğum sosyal gruplarda değersiz olduğumu hissederim.	Genel olarak, içinde bulunduğum sosyal grubun değerli olmadığını hissederim
-I feel good about the social groups I belong to.	İçinde bulunmak istediğim sosyal gruplar hakkında iyi hissederim.	Ait olduğum sosyal grup hakkında iyi hissederim.
-Overall, my social groups are considered good by others.	Genel olarak benim sosyal gruplarım başkaları tarafından iyi değerlendirilir.	Genel olarak sosyal grubum başkaları tarafından iyi değerlendirilir.
-Most people consider my social groups, on the average, to be more ineffective than other social groups.	Genel olarak daha fazla kişi, sosyal gruplarımın diğer sosyal gruplardan daha etkisiz olduğunu düşünür.	Çoğu kişi, sosyal grubumun diğer sosyal gruplardan daha etkisiz olduğunu düşünür.
-In general, others respect the social groups that I am a member of.	Genel anlamda, başkaları benim üyesi olduğum sosyal gruplara saygı duyar.	Genel anlamda, başkaları benim ait olduğum sosyal gruba saygı duyar.
-In general, others think that the social groups I am a member of are unworthy.	Genel olarak başkaları üyesi olduğum sosyal grupların değersiz olduğunu düşünürler.	Genel olarak başkaları benim sosyal grubumun değersiz olduğunu düşünürler.
-Overall, my group memberships have very little to do with how I feel about myself.	Genel olarak grup üyeleri benim kendim hakkında nasıl hissettiğimle çok az ilgililer.	Genel olarak içinde bulunduğum sosyal grubun benim kendimle ilgili nasıl hissettiğimle çok az bağlantısı var.
-he social groups I belong to are an important reflection of who I am.	-Ait olduğum sosyal gruplar, kim olduğumun önemli bir yansımasıdır.	Ait olduğum sosyal grup, kim olduğumun önemli bir yansımasıdır.
-The social groups I belong to are unimportant to my sense of what kind of a person I am.	Ait olduğum sosyal gruplar nasıl bir kişi olduğumla ilgili hissettiklerim açısından önemsizdir.	Ait olduğum sosyal grup, nasıl bir kişi olduğuma dair hislerim açısından önemsizdir.
-In general, belonging to social groups is an important part of my self-image.	Genel olarak, ait olduğum sosyal gruplar kendi imajımın önemli bir parçasıdır.	Genel olarak, ait olduğum sosyal grup kendi imajımın önemli bir parçasıdır.

Appendix E. Comparison of Survey Questionnaire Items Between This Dissertation and Source

Turkish Adaptation	Revised Item	
Kolektif Benlik Saygısı ()	Adopted for Gender Stereotypes by Author	Adopted for SES Stereotypes
Ait olduğum sosyal grubun değerli bir üyesiyim.	Ait olduğum cinsiyet grubunun (erkekler/kadınlar) değerli bir üyesiyim.	Ait olduğum sosyo ekonomik statü grubunun değerli bir üyesiyim.
Ait olduğum sosyal gruba fazla bir katkım olmadığını hissederim	Ait olduğum cinsiyet grubuna fazla bir katkım olmadığını hissederim	Ait olduğum sosyo ekonomik gruba fazla bir katkım olmadığını hissederim
Ait olduğum sosyal grubumda iş birliği içinde hareket ederim	Ait olduğum cinsiyet grubunda uyumlu bir katılımcıyım.	Ait olduğum sosyo-ekonomik statü grubunda iş birliği içinde hareket ederim
Çoğu zaman sosyal grubumda faydasız olduğumu hissederim.	Çoğu zaman, ait olduğum cinsiyet grubunda faydasız olduğumu hissederim	Çoğu zaman ait olduğum sosyo ekonomik statü grubunda faydasız olduğumu hissederim.
İçinde bulunduğum sosyal gruba dahil olduğum için zaman zaman pişmanlık duyuyorum.	Ait olduğum cinsiyet grubuna mensup olmaktan çoğu zaman pişmanlık duyarım	Yer aldığım sosyo ekonomik statü grubuna dahil olduğum için zaman zaman pişmanlık duyuyorum.
Genel olarak, ait olduğum sosyal grupta olmaktan memnunum.	Genel olarak, erkekler/ kadınlar grubuna ait olmaktan memnunum.	Genel olarak, ait olduğum sosyoekonomik statü grubunda olmaktan memnunum
Genel olarak, içinde bulunduğum sosyal grubun değerli olmadığını hissederim	Genel olarak, ait olduğum cinsiyet grubunun değerli olmadığını hissederim	Genel olarak, içinde bulunduğum sosyo ekonomik statü grubunun değerli olmadığını hissederim.
Ait olduğum sosyal grup hakkında iyi hissederim.	Ait olduğum cinsiyet grubu hakkında iyi hissederim	Ait olduğum sosyo ekonomik statü grubu hakkında iyi hissederim.
Genel olarak sosyal grubum başkaları tarafından iyi değerlendirilir.	Genel olarak, başkaları benim cinsiyet grubumu(kadınları/erkekleri) olumlu değerlendirir.	Genel olarak benim sosyo ekonomik statü grubum başkaları tarafından olumlu değerlendirilir.
Çoğu kişi, sosyal grubumun diğer sosyal gruplardan daha etkisiz olduğunu düşünür.	Çoğu kişi, cinsiyet grubumun diğerine kıyasla daha etkisiz olduğunu düşünür.	Çoğu kişi, benim sosyo ekonomik statü grubumun diğer gruplardan daha etkisiz olduğunu düşünür.
Genel anlamda, başkaları benim ait olduğum sosyal gruba saygı duyar.	Genel olarak, başkaları benim cinsiyet grubuma (kadınlara/erkeklere) saygı duyar.	Genel anlamda, başkaları benim ait olduğum sosyo ekonomik statü grubuna saygı duyar.
Genel olarak başkaları benim sosyal grubumun değersiz olduğunu düşünürler.	Genel olarak, başkaları benim cinsiyet grubumu (kadınları/erkekleri) değersiz olarak görür.	Genel olarak başkaları, benim sosyo ekonomik statü grubumu değersiz bulur.
Genel olarak içinde bulunduğum sosyal grubun kendimle ilgili nasıl hissettiğimle çok az ilgisi var.	Genel olarak, cinsiyetimin kendimle ilgili nasıl hissettiğimle çok az ilgisi var.	Genel olarak, içinde bulunduğum sosyoekonomik grubun benim kendimle ilgili nasıl hissettiğimle çok az bağlantısı var.
Ait olduğum sosyal grup, kim olduğumun önemli bir yansımasıdır.	Ait olduğum cinsiyet grubu, kim olduğumun önemli bir yansımasıdır.	Ait olduğum sosyo ekonomik statü grubu, kim olduğumun önemli bir yansımasıdır.
Ait olduğum sosyal grup, nasıl bir kişi olduğuma dair hislerim açısından önemsizdir.	Ait olduğum cinsiyet grubu, nasıl bir kişi olduğuma dair hislerim açısından önemsizdir.	Ait olduğum sosyo ekonomik statü grup, nasıl bir kişi olduğuma dair hislerim açısından önemsizdir.
Genel olarak, ait olduğum sosyal grup kendi imajımın önemli bir parçasıdır.	Genel olarak, cinsiyetime ait olmak (kadın/erkek olmak), kendi imajımın önemli bir parçasıdır.	Genel olarak, ait olduğum sosyo ekonomik statü grubu, kendi imajımın önemli bir parçasıdır.

Appendix F. Adopted Scales – Translated-Back Translated

Dissociative Concerns (White & Dahl 2006)	-	Türkçe Çeviri	
I dislike the association of this product.	-	Bu önerilerin çağrıştırdıklarını beğenmiyorum	
I want to avoid being associated with this product.	-	Bu önerilerle bağdaştırılmaktan kaçınmak isterim	
This product reflects who I do not want to be.	-	Bu öneriler, olmak istemediğim bir imajı yansıtıyor	

Social Identity Threat -Adopted from Homburg and Ukrainets developed from (Steele et al., 2002) (White & Argo,2009).	Sosyal Kimlik Tehdidi–Yeniçeri & Uzuner 2022	Adaptasyon–Human	Adaptasyon- AI
The fact that my friend saw me with this product undermined my identity.	Arkadaşımın beni bir indirim mağazasının çantasıyla görmesi, kimliğimi zedeledi.	Satış danışmanının benim için uygun olduğunu düşünerek önerdiği bu ürünlerle arkadaşımın beni görmesi, kimliğimi zedeler	Alışveriş uygulamasının “Sana Özel Ürünler” başlığı altında bu ürünleri bana önermesi kimliğimi zedeler
My personality was challenged when my friends saw me buying this product	Arkadaşım beni bir indirim mağazasının çantasını tutarken görünce kişiliğime meydan okundu.	Satış danışmanı benim için uygun olduğunu düşündüğü bu ürünleri önerirken arkadaşımın beni görmesi kişiliğime meydan okunmasına sebep olur,	Alışveriş uygulamasının “Sana Özel Ürünler” başlığı altında bu ürünleri bana önermesi kişiliğime meydan okunmasına sebep olur
The fact that my friend saw me buying this product threatened the way I feel about myself	Arkadaşımın beni bir indirim mağazasının çantasıyla görmesi, kendimle ilgili hislerimi tehdit etti.	Satış danışmanı benim için uygun olduğunu düşündüğü bu ürünleri önerirken arkadaşımın beni görmesi, kendimi tehdit altında hissetmeme sebep olur	Alışveriş uygulamasının “Sana Özel Ürünler” başlığı altında bana bu ürünleri önermesi kendimi tehdit altında hissetmeme sebep olur

Appendix G. Experimental Stimuli & Images- Pretest – S.E.S. Signaling Content

Recommender Type: Human

Associative Recommender Group – All Genders	**Dissociative Recommender Group –All Genders**
Her zaman alışveriş yaptığınız, erişilebilir lüks kategorisindeki yerli ve yabancı markaların yanı sıra uygun fiyatlı markaların da bulunduğu büyük bir perakende satış mağazasına gittiğinizi düşünün. Son zamanlarda artan enflasyon ve düşen alım gücü nedeniyle alışveriş alışkanlıklarınızda değişiklik yaptınız; önceki tercihleriniz olan yüksek fiyatlı ürünleri sezonda almaktan kaçınarak indirimleri beklemeye veya daha ekonomik seçeneklere yönelmeye başladınız. Geçtiğimiz günlerde bu mağazadan, standart bir beyaz oversize tişört ararken, lüks markalar yerine fiyat-fayda dengesi yüksek ve uygun fiyatlı bir ürünü satın aldınız. Bugün satın aldığınız beyaz tshirt'ü giyerek tekrar mağazaya alışveriş yapmaya gidiyorsunuz. İlginizi çeken modellerin bedenlerini ve renklerini inceliyor, almayı düşündüğünüz birkaç tanesini şimdilik elinizde tutuyorsunuz. Üzerinizdeki t-shirt'in hangi markaya ait olduğunu bilen ve elinizdeki ürünleri inceleyen satış danışmanı, size **”*Bunlar da ilginizi çekebilir*”** diyerek birkaç seçenek ile yanınıza geliyor.	Her zaman alışveriş yaptığınız, erişilebilir lüks kategorisindeki yerli ve yabancı markaların yanı sıra uygun fiyatlı markaların da bulunduğu büyük bir perakende satış mağazasına gittiğinizi düşünün. Son zamanlarda artan enflasyon ve düşen alım gücü nedeniyle alışveriş alışkanlıklarınızda değişiklik yaptınız; önceki tercihleriniz olan yüksek fiyatlı ürünleri sezonda almaktan kaçınarak indirimleri beklemeye veya daha ekonomik seçeneklere yönelmeye başladınız. Geçtiğimiz günlerde bu mağazadan, standart bir beyaz oversize tişört ararken, lüks markalar yerine fiyat-fayda dengesi yüksek ve uygun fiyatlı bir ürünü satın aldınız. Bugün satın aldığınız beyaz t-shirt'i giyerek tekrar mağazaya gittiğinizde, göz attığınız bazı ürünleri incelerken satış danışmanı size yaklaşıyor. Üzerinizdeki t-shirt'in hangi markaya ait olduğunu bilen ve elinizdeki ürünleri inceleyen satış danışmanı, <u>bütçenize daha uygun olabileceğini düşündüğü</u> bazı seçenekleri öneriyor. Size nazik bir şekilde **”*Eğer isterseniz, daha uygun fiyatlı ürünlere de göz atabilirsiniz,*”** diyerek <u>mağazanın sezon sonu ürünlerinden</u> birkaç seçenek gösteriyor.
Size özel sunulan bu ürünleri gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.	Size özel sunulan bu ürünleri gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.

Recommender Type: AI - Female

<table>
<tr><th>Associative Recommender Group</th><th>Dissociative Recommender Group</th></tr>
<tr><td colspan="2">E-ticaret platformları çoğunluğunda, kullanıcı deneyimini kişiselleştirmek ve alışveriş süreçlerini hızlandırmak amacıyla yapay zekâ tabanlı öneri sistemleri kullanır. Bu sistemler, kullanıcıların geçmişteki davranışlarını (arama geçmişi, tıklamalar, satın alma işlemleri, favorilere eklenen ürünler vb.), tercihlerini (beden, renk, fiyat aralığı vb.) ve eğer kullanıcı tarafından verilmişse demografik bilgilerini (yaş, cinsiyet vb.) analiz eder. Bu analizlerden kalıplar ve ilişkiler çıkarmayı öğrenir ve elde edilen tüm bilgiler doğrultusunda sınıflandırarak kullanıcının ihtiyaç ve beğenilerine uygun ürün veya içerik önerileri sunar.
Kullanıcı davranışı değiştikçe, sistem yeni davranışları öğrenir ve önerilerini buna göre günceller. Ancak, kullanıcı davranışları değişmeden, <u>bu öneri çemberinin dışına çıkmak neredeyse imkansızdır.</u></td></tr>
<tr><td>Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün.
Son zamanlarda artan enflasyon ve düşen alım gücü nedeniyle alışveriş alışkanlıklarınızda küçük değişiklikler yaparak, uygun fiyatlı ancak kaliteli ürünlere yönelmeye başladınız. Fakat önceki tercihlerinizden ödün vermek istemiyorsunuz.
Geçen hafta, bu platformda beyaz bir oversize tişört ararken her zamanki markalarınızdan biri yerine bütçenize uygun bir seçenek tercih ettiniz.
Bugün uygulamayı tekrar açtığınızda, "Sana Özel" başlığı altında geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerle karşılaşıyorsunuz. Bu bölümde, hem daha önce tercih ettiğiniz markalar (örneğin İpekyol, Network, Machka, Yargıcı) hem de bütçenize uygun yeni markalar bulunuyor. <u>(Lütfen görselleri dikkatlice inceleyin)</u></td><td>Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün.
Son zamanlarda artan enflasyon ve düşen alım gücü nedeniyle alışveriş alışkanlıklarınızda değişiklik yaptınız; önceki tercihleriniz olan yüksek fiyatlı ürünleri sezonda almaktan kaçınarak indirimleri beklemeye veya daha ekonomik seçeneklere yönelmeye başladınız.
Geçen hafta da beyaz bir oversize tişört ararken, tercih ettiğiniz markalardan ziyade fiyat-fayda dengesi yüksek ve uygun fiyatlı bir ürünü, daha önce adını duymadığınız bir mağazadan satın aldınız.
Uygulamayı bugün tekrar açtığınızda, geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerin yer aldığı "Sana Özel" başlığı altında, daha önce tercih ettiğiniz erişilebilir lüks kategorisindeki markalar yerine ağırlıklı olarak daha önce tercih etmediğiniz markaların ya da hiç duymadığınız butiklerin uygun fiyatlı ve indirimli ürünlerle karşılaşıyorsunuz. <u>(Lütfen görselleri dikkatlice inceleyin)</u>
Ek olarak daha önce "Sana Özel Markalar" ve "En Yeniler" bölümü <u>yerine</u> "Bütçe Dostu Ürünler" ve "ikinci el" bölümlerini görüyorsunuz.</td></tr>
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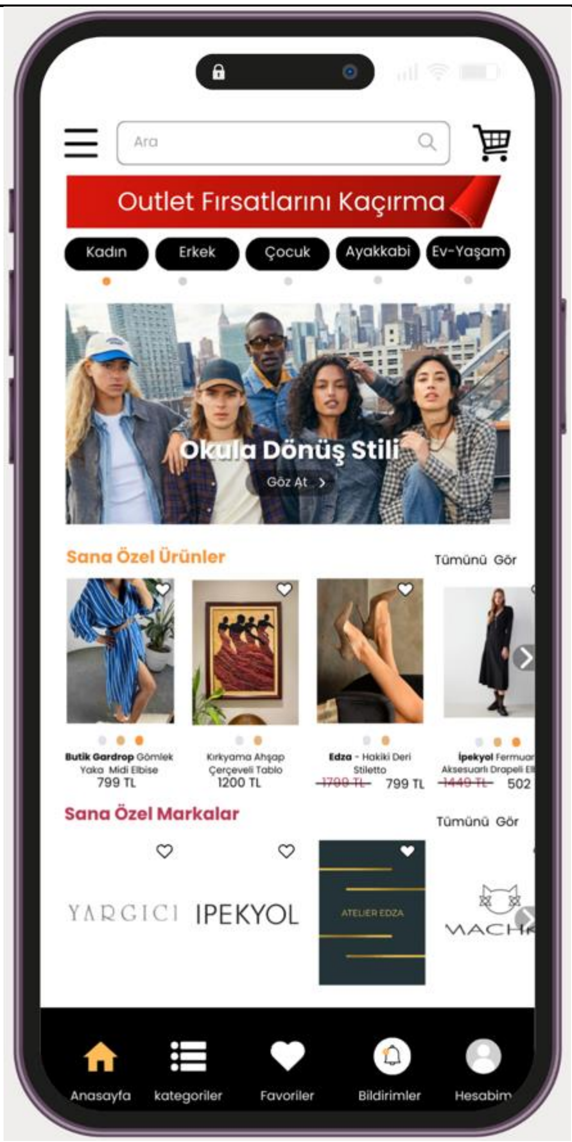
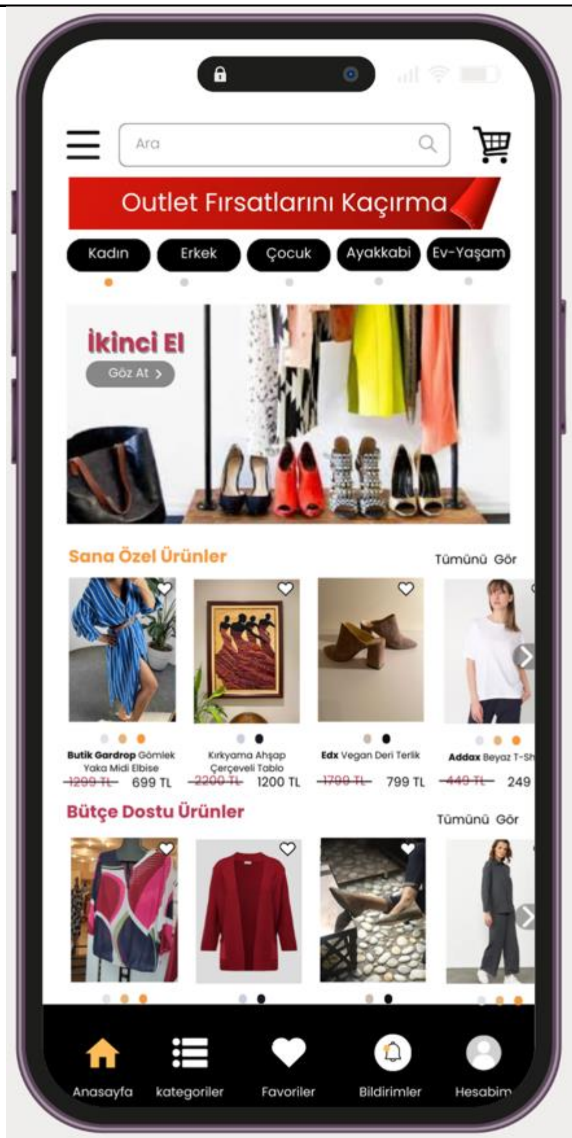
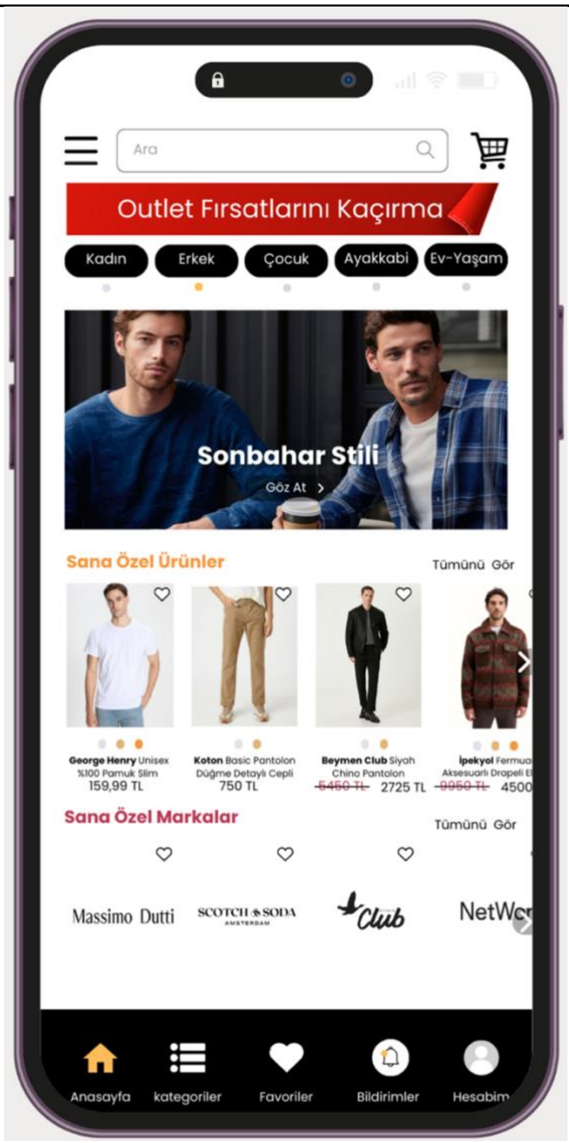


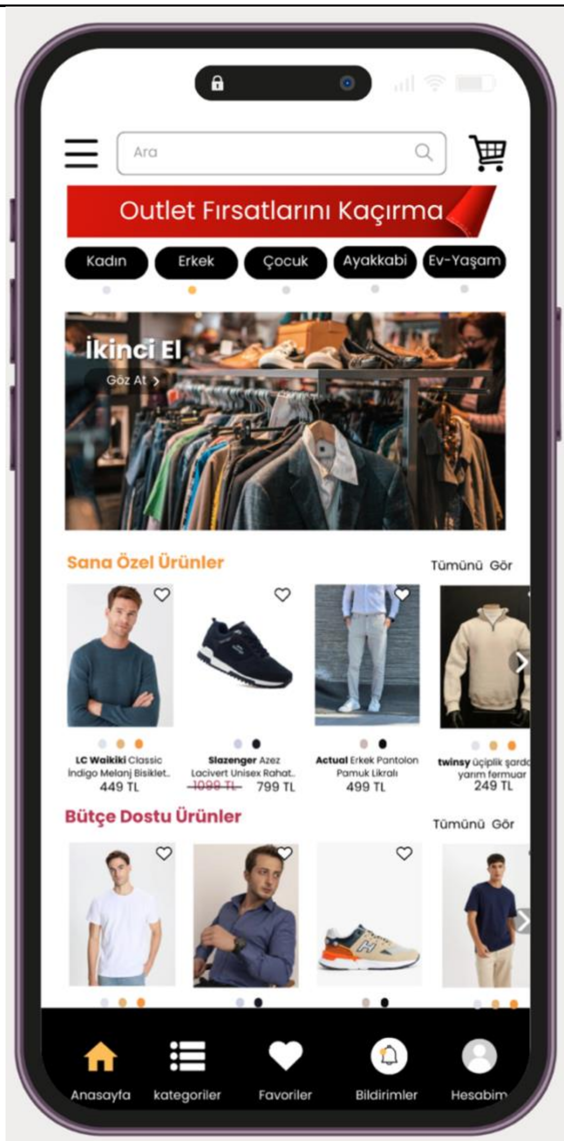


Size özel sunulan kişiselleştirilmiş bu önerileri gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.	Size özel sunulan kişiselleştirilmiş bu önerileri ve uygulama ekranını gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.

Recommender Type: AI Male

Associative Recommender Group	Dissociative Recommender Group
E-ticaret platformları çoğunluğunda, kullanıcı deneyimini **kişiselleştirmek** ve alışveriş süreçlerini hızlandırmak amacıyla **yapay zekâ tabanlı öneri sistemleri** kullanır. Bu sistemler, kullanıcıların **geçmişteki davranışlarını** (arama geçmişi, tıklamalar, satın alma işlemleri, favorilere eklenen ürünler vb.), **tercihlerini** (beden, renk, fiyat aralığı vb.) ve eğer kullanıcı tarafından verilmişse **demografik bilgilerini** (yaş, cinsiyet vb.) **analiz eder**. Bu analizlerden kalıplar ve ilişkiler çıkarmayı öğrenir ve elde edilen tüm bilgiler doğrultusunda **sınıflandırarak** kullanıcının ihtiyaç ve beğenilerine uygun **ürün veya içerik önerileri sunar.** **Kullanıcı davranışı değiştikçe**, sistem yeni davranışları **öğrenir** ve önerilerini buna göre **günceller**. **Ancak**, kullanıcı **davranışları değişmeden**, **<u>bu öneri çemberinin dışına çıkmak neredeyse imkansızdır.</u>**	
Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün. Son zamanlarda artan enflasyon ve düşen alım gücü nedeniyle alışveriş alışkanlıklarınızda küçük değişiklikler yaparak, uygun fiyatlı ancak kaliteli ürünlere yönelmeye başladınız. Fakat önceki tercihlerinizden ödün vermek istemiyorsunuz. Geçen hafta, bu platformda beyaz bir tişört ararken her zamanki markalarınızdan biri yerine bütçenize uygun bir seçenek tercih ettiniz. Bugün uygulamayı tekrar açtığınızda, ***"Sana Özel"*** başlığı altında geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerle karşılaşıyorsunuz. Bu bölümde, hem daha önce tercih ettiğiniz markalar (örneğin İpekyol, Network, Machka, Yargıcı) hem de bütçenize uygun yeni markalar bulunuyor. *<u>(Lütfen görselleri dikkatlice inceleyin)</u>*	Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün. Son zamanlarda artan enflasyon ve düşen alım gücü nedeniyle alışveriş alışkanlıklarınızda değişiklik yaptınız; önceki tercihleriniz olan yüksek fiyatlı ürünleri sezonda almaktan kaçınarak indirimleri beklemeye veya daha ekonomik seçeneklere yönelmeye başladınız. Geçen hafta da beyaz bir tişört ararken, tercih ettiğiniz markalardan ziyade fiyat-fayda dengesi yüksek ve uygun fiyatlı bir ürünü, daha önce adını duymadığınız bir mağazadan satın aldınız. Uygulamayı bugün tekrar açtığınızda, geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerin yer aldığı **"Sana Özel"** başlığı altında, daha önce tercih ettiğiniz erişilebilir lüks kategorisindeki markalar yerine ağırlıklı olarak daha önce tercih etmediğiniz markaların ya da hiç duymadığınız butiklerin uygun fiyatlı ve indirimli ürünlerle karşılaşıyorsunuz. *<u>(Lütfen görselleri dikkatlice inceleyin)</u>* Ek olarak daha önce **"Sana Özel Markalar"** ve **"En Yeniler"** bölümü *<u>yerine</u>* **"Bütçe Dostu Ürünler"** ve **"ikinci el"** bölümlerini görüyorsunuz.





Size özel sunulan kişiselleştirilmiş bu önerileri gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.

Size özel sunulan kişiselleştirilmiş bu önerileri ve uygulama ekranını gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.

Appendix H. Study 1: Age Stereotype Signaling Contents

Recommender Type: Human - Female

Associative Recommender Group	**Dissociative Recommender Group**
Hormonsal değişikliklerden ötürü sık sık sıcak basıyor ve gece terleme sorunu yaşamaya başladınız. Araştırdığınızda oda sıcaklığını değiştirmek gibi önerilerin yanı sıra yatarken ince ve pamuklu kıyafetler tercih etmeniz tavsiye ediliyor. Bu nedenle her zaman alışveriş yaptığınız bir mağazaya giderek terletmeyen gecelikler ve %100 pamuklu pijamalar arıyorsunuz. İlginizi çeken modellerin kumaşını ve yapısını inceliyor, almayı düşündüğünüz birkaç tanesini şimdilik elinizde tutuyorsunuz. Elinizdeki ürünleri inceleyen ve pamuklu ürünler aradığınızı anlayan satış temsilcisi size yaklaşıyor. Satış temsilcisine geceleri terlediğinizi bu sebeple terletmeyen ürünler aradığınızı belirtiyorsunuz. Kendisi de size Femti markasının kolajen içeren kumaşıyla rahatlık sağlayan yeni serisinin aşağıda göreceğiniz mağaza içi afişlerini göstererek ürünlerini öneriyor. <u>*(Lütfen görselleri dikkatlice inceleyin)*</u> Size dönerek, "Bu ürün, Kolajen içeren kumaşın nem tutuculuğu sayesinde teri vücuttan uzaklaştırır, giyildiği süre boyunca serin tutar." diyerek devam ediyor. "Pijama takımının fiyatı 1999 TL, geceliğin fiyatı 1299 TL.	Hormonsal değişikliklerden ötürü sık sık sıcak basıyor ve gece terleme sorunu yaşama başladınız. Araştırdığınızda oda sıcaklığını değiştirmek gibi önerilerin yanı sıra yatarken ince ve pamuklu kıyafetler tercih etmeniz tavsiye ediliyor. Bu nedenle her zaman alışveriş yaptığınız bir mağazaya giderek terletmeyen gecelikler ve %100 pamuklu pijamalar arıyorsunuz. İlginizi çeken modellerin kumaşını ve yapısını inceliyor, almayı düşündüğünüz birkaç tanesini şimdilik elinizde tutuyorsunuz. Elinizdeki ürünleri inceleyen ve pamuklu ürünler aradığınızı anlayan satış temsilcisi size yaklaşıyor. Satış temsilcisine geceleri terlediğinizi bu sebeple terletmeyen ürünler aradığınızı belirtiyorsunuz. Kendisi de size Femti markasının kolajen içeren kumaşıyla rahatlık sağlayan menopoz dönemine özel Aging serisinin aşağıda göreceğiniz mağaza içi afişlerini göstererek ürünlerini öneriyor. <u>*(Lütfen görselleri dikkatlice inceleyin)*</u> Size dönerek, "Bu ürün, Kolajen içeren kumaşın nem tutuculuğu sayesinde teri vücuttan uzaklaştırır, yaşlanma belirtilerinin yanı sıra sıcak basması, gece terlemesi gibi menopoz etkilerini de azaltarak giyildiği süre boyunca serin tutar." diyerek devam ediyor. "Pijama takımının fiyatı 1999 TL, geceliğin fiyatı 1299 TL.
	

Price Condition

Bu aşamada satış temsilcisi, size gösterdiği ürünlerde lansmana özel kasada geçerl**i %50 indirimde** olduğunu hatırlıyor ve ekliyor *”Bu ürünler şu anda lansmana özel kısa bir süre için %50 indirimde. Pijama takımının fiyatı kasada **1999 TL'**den **999 TL'**ye, geceliğin fiyatı **1299 TL**'den **649 TL**'ye inecek.*

Price Condition

Bu aşamada satış temsilcisi, size gösterdiği ürünlerde lansmana özel kasada geçerl**i %50 indirimde** olduğunu hatırlıyor ve ekliyor *”Bu ürünler şu anda lansmana özel kısa bir süre için %50 indirimde. Pijama takımının fiyatı kasada **1999 TL'**den **999 TL'**ye, geceliğin fiyatı **1299 TL**'den **649 TL**'ye inecek.*

Recommender Type: Human - Male

Associative Reference Group	Dissociative Reference Group
Her zaman alışveriş yaptığınız büyük bir perakende satış mağazasına gittiğinizi düşünün. Geçmişte bu mağazanın erkek reyonundan yaz sezonunda şapka, kış aylarında ise deri eldiven ve kaşkol gibi tarzınıza uygun çeşitli aksesuarlar satın aldınız. Son zamanlarda, soğuk ve yağmurlu havalarda kullanmak üzere bir şapka arayışı içindesiniz. Şapka, bere veya kasket gibi seçenekleri değerlendirirken, izlediğiniz popüler dizilerden ve karşılaştığınız bazı reklamlardan etkilenerek kasket modellerini incelemeye karar verdiniz. Kasket modellerini inceliyor ve ilginizi çekenleri deniyorsunuz. Bu sırada bir satış danışmanı yanınıza gelerek, ”Bu ürünler de ilginizi çekebilir” diyerek, aşağıda göreceğiniz mağaza içi afişlerdeki ürünleri öneriyor *(lütfen görselleri dikkatlice inceleyin).* Ardından, ”Özellikle dizilerden sonra moda haline geldi. Brad Pitt ve David Beckham’ın çok tercih ettiği bir model,” diye ekliyor.	Her zaman alışveriş yaptığınız bir perakende satış mağazasına gittiğinizi düşünün. Geçmişte bu mağazanın erkek reyonundan yaz aylarında şapka, kış aylarında ise deri eldiven ve kaşkol gibi tarzınıza uygun çeşitli aksesuarlar satın aldınız. Son dönemde, soğuk ve yağmurlu havalarda kullanmak üzere bir şapka arıyorsunuz. Şapka, bere veya kasket gibi seçenekler üzerinde düşünürken, izlediğiniz popüler dizilerden ve karşılaştığınız bazı reklamlardan etkilenerek kasket modellerini incelemeye karar verdiniz. Mağazada çeşitli kasket modellerini inceliyor ve ilginizi çekenleri deniyorsunuz. Bu sırada bir satış danışmanı yanınıza gelerek, ”Bu ürünler de ilginizi çekebilir” diyerek aşağıda göreceğiniz mağaza içi afişlerdeki ürünleri öneriyor *(lütfen görselleri dikkatlice inceleyin).* Ardından satış danışmanı, ”Bu model klasik, ama özellikle soğuk havalarda çok sıcak tutar. Müşterilerimiz bu modelden oldukça memnun. Hatta bir müşterimiz geçen gün babası için bu modelden aldı ve birkaç gün sonra farklı bir rengini de satın aldı,” diyor.
	

Price Condition

Bu aşamada satış temsilcisi, size önerdiği ürünlerin bazılarında indirim olduğunu hatırlıyor ve ekliyor *”Bu ürün şu anda bugüne özel indirimde. Fiyatı kasada* ***1099 TL****'den* ***499TL****'ye inecek. “*

Price Condition

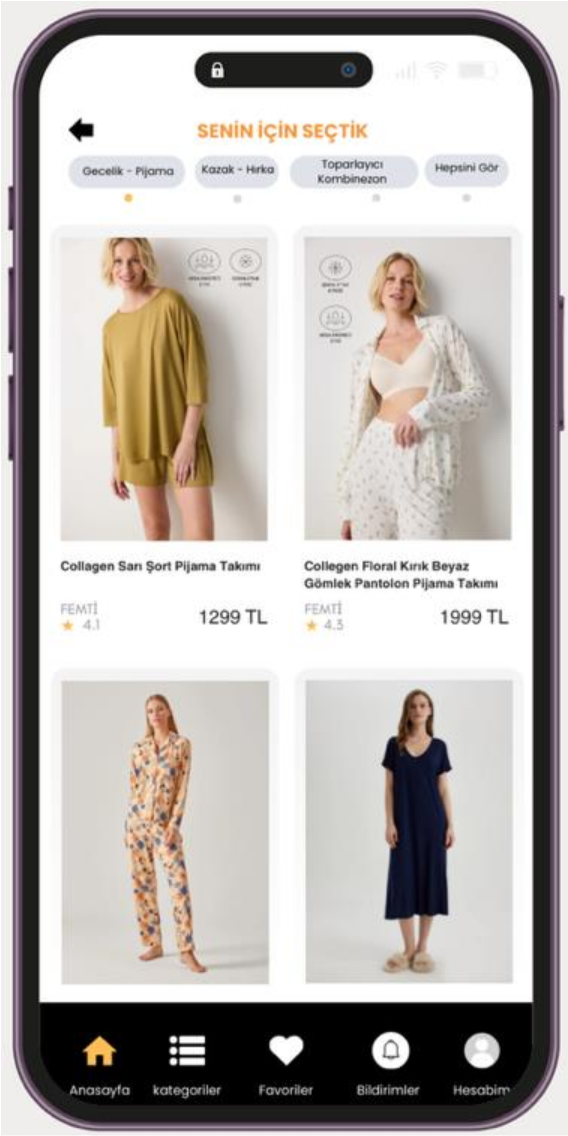
Bu aşamada satış temsilcisi, size önerdiği ürünlerin bazılarında indirim olduğunu hatırlıyor ve ekliyor *”Bu ürün şu anda bugüne özel indirimde. Fiyatı kasada* ***1099 TL****'den* ***499TL****'ye inecek. “*

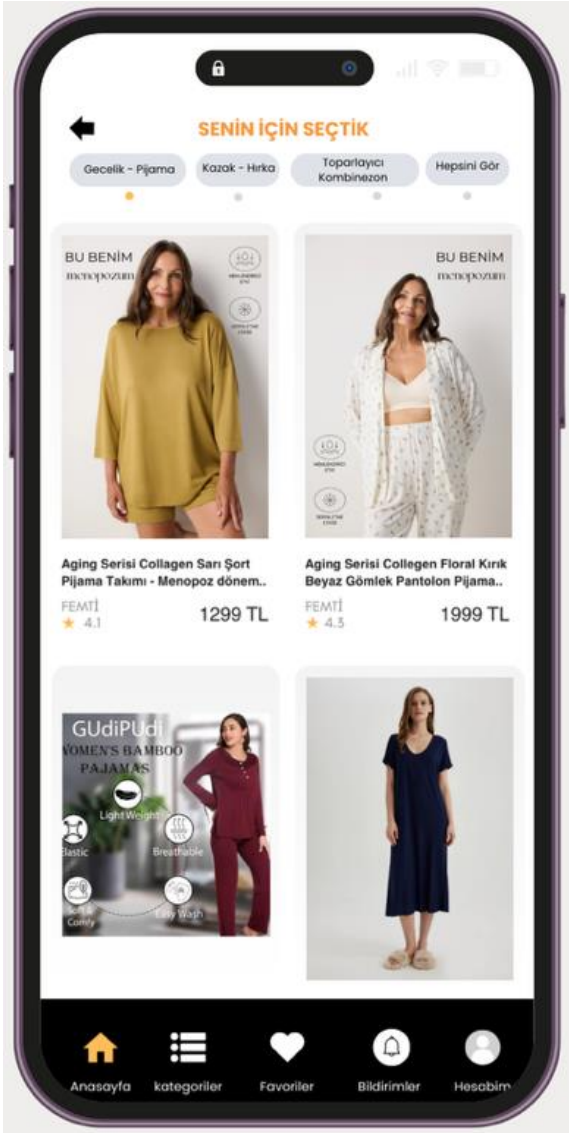
Recommender Type: AI - Female

E-ticaret platformları *çoğunlukla, kullanıcı deneyimini* ***kişiselleştirmek*** *ve alışveriş süreçlerini hızlandırmak amacıyla* ***yapay zekâ tabanlı öneri sistemleri*** *kullanır. Bu sistemler, kullanıcıların* ***geçmişteki davranışlarını*** *(arama geçmişi, tıklamalar, satın alma işlemleri, favorilere eklenen ürünler vb.),* ***tercihlerini*** *(beden, renk, fiyat aralığı vb.) ve eğer kullanıcı tarafından verilmişse* ***demografik bilgilerini*** *(yaş, cinsiyet vb.)* ***analiz eder****. Bu analizlerden kalıplar ve ilişkiler çıkarmayı öğrenir ve elde edilen tüm bilgiler doğrultusunda* ***<u>sınıflandırarak</u>*** *kullanıcının ihtiyaç ve beğenilerine uygun* ***ürün veya içerik önerileri sunar.*** ***Kullanıcı davranışı değiştikçe****, sistem yeni davranışları* ***öğrenir*** *ve önerilerini buna göre* ***günceller****.* ***Ancak****, kullanıcı* ***davranışları değişmeden****,* **<u>bu öneri çemberinin dışına çıkmak neredeyse imkansızdır.</u>**

Associative Recommender Group	**Dissociative Recommender Group**
Şimdi sıklıkla kullandığınız (ürün aradığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün. Hormonsal değişimlerden kaynaklanan gece terlemeleri yaşıyorsunuz. Araştırdığınızda, oda sıcaklığını değiştirmek gibi önerilerin yanı sıra <u>yatarken ince ve pamuklu kıyafetler tercih etmeniz tavsiye ediliyor</u>. Bu doğrultuda, sıklıkla alışveriş yaptığınız bir uygulamadan **"terletmeyen gecelik", "terletmeyen pijama", "pamuklu pijama"** gibi ürünler aradınız. Belirli bir incelemeden sonra **"Nefes Alan Terletmeyen Kadın Pijama Takımı"** satın aldınız.	Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün. Hormonsal değişikliklerden ötürü sık sık sıcak basıyor ve gece terleme sorunu yaşıyorsunuz. Araştırdığınızda oda sıcaklığını değiştirmek gibi önerilerin yanı sıra yatarken ince ve pamuklu kıyafetler tercih etmeniz tavsiye ediliyor. Bu doğrultuda sıklıkla alışveriş yaptığınız bir uygulamadan "terletmeyen gecelik", "pamuklu pijama" gibi ürünler aramış, belirli bir inceleme aşamasından sonra **Nefes Alan Terletmeyen Kadın Pijama Takımı** satın almıştınız.

	
Bildirim ekranını açtığınızda, aşağıdaki ekranda Femti markasının kolajen içeren kumaşıyla rahatlık ve serinlik sağlayan özel serisinin parçalarının da olduğu ürünleri görüyorsunuz. *(Aşağıdaki ürünlerin görsellerine, fiyatına ve ürün adına dikkatlice bakmanızı rica ederiz.)*	Bildirim ekranını açtığınızda aşağıdaki ekranda Femti markasının “Aging” serisinden kolajen içeren kumaşıyla rahatlık ve serinlik sağlayan özel serisinin parçalarının da olduğu ürünleri görüyorsunuz. *(Aşağıdaki ürünlerin görsellerine, fiyatına ve ürün adına dikkatlice bakmanızı rica ederiz.*





Size özel sunulan bu ürünleri gördüğünüzde hissettiklerinizi ve önerilen ürünlerin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ediyoruz.	Size özel sunulan bu ürünleri gördüğünüzde hissettiklerinizi ve önerilen ürünlerin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ediyoruz.
Price Condition Aynı gün içinde uygulamada gezerken, size önerilen ürünlerden aşağıdaki ürünün **%50 indirime** girdiğini fark ettiniz.	**Price Condition** Aynı gün içinde uygulamada gezerken, size önerilen ürünlerden aşağıdaki ürünün **%50 indirime** girdiğini fark ettiniz.


Ara
NEMLENDİRİCİ ETKİ
SERİNLETME ETKİSİ
KOLAJEN İÇERİKLİ
FEMTİ Collegen Floral Kırık Beyaz Gömlek Pantolon Pijama Takımı
4.3
~~1999~~ TL 999 TL
SEPETE EKLE
Anasayfa
kategoriler
Favoriler
Bildirimler
Hesabım

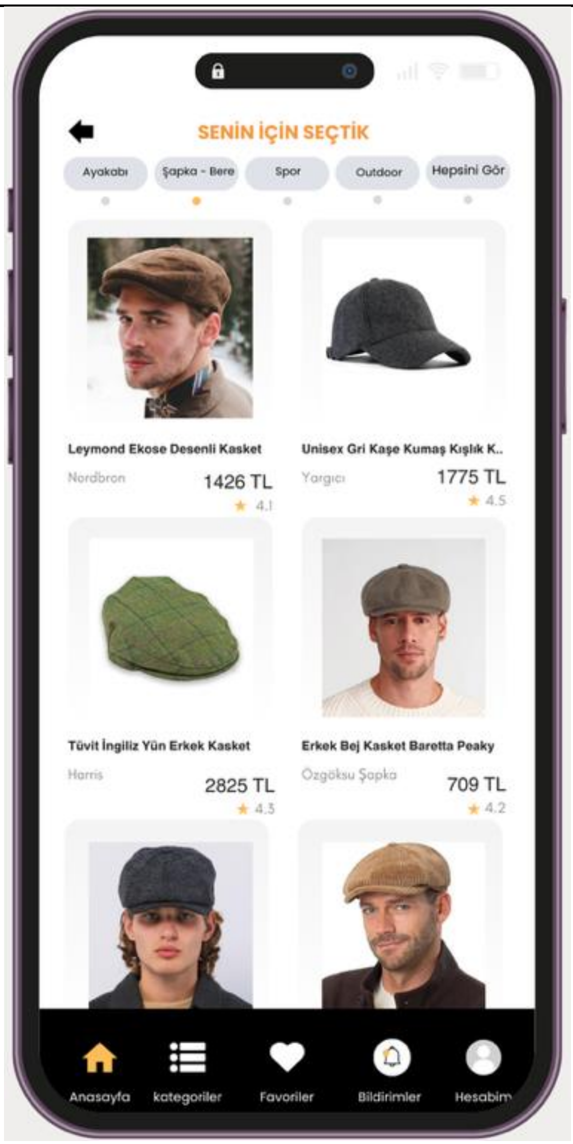
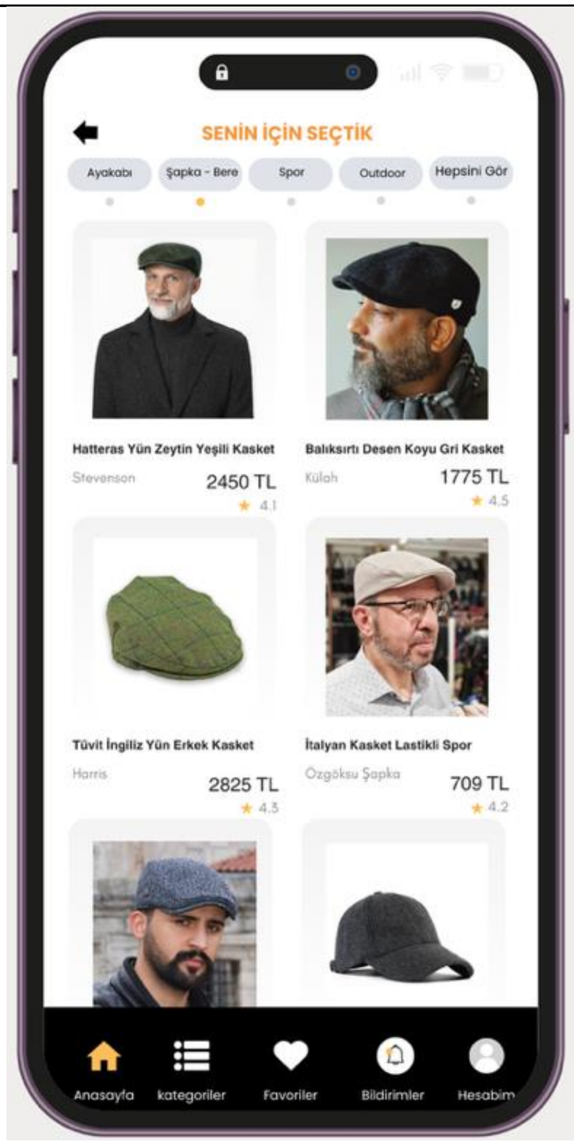

Ara
NEMLENDİRİCİ ETKİ
SERİNLETME ETKİSİ
KOLAJEN İÇERİKLİ
FEMTİ Aging Serisi Collegen Floral Kırık Beyaz Gömlek Pantolon Pijama Takımı - Menopoz dönemine özel
4.3
~~1999~~ TL 999 TL
SEPETE EKLE
Anasayfa
kategoriler
Favoriler
Bildirimler
Hesabım

Recommender Type: AI - Male

E-ticaret platformları** çoğunlukla, kullanıcı deneyimini **kişiselleştirmek** ve alışveriş süreçlerini hızlandırmak amacıyla **yapay zekâ tabanlı öneri sistemleri** kullanır. Bu sistemler, kullanıcıların **geçmişteki davranışlarını** (arama geçmişi, tıklamalar, satın alma işlemleri, favorilere eklenen ürünler vb.), **tercihlerini** (beden, renk, fiyat aralığı vb.) ve eğer kullanıcı tarafından verilmişse **demografik bilgilerini** (yaş, cinsiyet vb.) **analiz eder**. Bu analizlerden kalıplar ve ilişkiler çıkarmayı öğrenir ve elde edilen tüm bilgiler doğrultusunda **sınıflandırarak** kullanıcının ihtiyaç ve beğenilerine uygun **ürün veya içerik önerileri sunar.** **Kullanıcı davranışı değiştikçe**, sistem yeni davranışları **öğrenir** ve önerilerini buna göre **günceller**. **Ancak**, kullanıcı **davranışları değişmeden**, **bu öneri çemberinin dışına çıkmak neredeyse imkansızdır.

Associative Recommender Group	**Dissociative Recommender Group**
Şimdi sıklıkla kullandığınız (ürün aradığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı hayal edin. Geçmişte "Erkek Aksesuar" kategorisinden, yaz sezonunda şapka; kış aylarında ise deri eldiven, kaşkol gibi çeşitli ürünler satın almıştınız. Son zamanlarda, soğuk ve yağmurlu havalarda kullanmak üzere tarzınıza uygun bir şapka arayışı içindesiniz. İzlediğiniz popüler dizilerden ve karşılaştığınız bazı reklamlardan etkilenerek **"şapka", "kasket"** gibi aramalar yaptınız ve ağırlıklı olarak **kasket** modellerini incelediniz.	Şimdi sıklıkla kullandığınız (ürün aradığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı hayal edin. Geçmişte "Erkek Aksesuar" kategorisinden, yaz sezonunda şapka; kış aylarında ise deri eldiven, kaşkol gibi çeşitli ürünler satın almıştınız. Son zamanlarda, soğuk ve yağmurlu havalarda kullanmak üzere tarzınıza uygun bir şapka arayışı içindesiniz. İzlediğiniz popüler dizilerden ve karşılaştığınız bazı reklamlardan etkilenerek **"şapka", "kasket"** gibi aramalar yaptınız ve ağırlıklı olarak **kasket** modellerini incelediniz.
Bugün e-ticaret platformundan sizin önceki aramalarınız, tercihleriniz ve demografik bilgileriniz analiz edilerek oluşturulmuş aşağıdaki bildirimi aldınız.	Bugün e-ticaret platformundan sizin önceki aramalarınız, tercihleriniz ve demografik bilgileriniz analiz edilerek oluşturulmuş aşağıdaki bildirimi aldınız.

Bildirim ekranını açtığınızda, geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerin yer aldığı **”SENİN İÇİN SEÇTİK”** başlığı altında aşağıdaki ekran ile karşılaşıyorsunuz. (Lütfen görselleri ve fiyatları dikkatlice inceleyiniz.)	Bildirim ekranını açtığınızda, geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerin yer aldığı **”SENİN İÇİN SEÇTİK”** başlığı altında aşağıdaki ekran ile karşılaşıyorsunuz. (Lütfen görselleri ve fiyatları dikkatlice inceleyiniz.)

	
Price Condition Aynı gün içinde uygulamada gezerken, size önerilen ürünlerden aşağıdaki ürünün **büyük indirime** girdiğini fark ettiniz.,	**Price Condition** Aynı gün içinde uygulamada gezerken, size önerilen ürünlerden aşağıdaki ürünün **büyük indirime** girdiğini fark ettiniz.


Ara
Özgöksu Şapka İtalyan Kasket Balıksırtı Gri Kışlık Kasket
4.3
~~709 TL~~ 299 TL
SEPETE EKLE
Anasayfa
kategoriler
Favoriler
Bildirimler
Hesabim


Ara
Özgöksu Şapka İtalyan Kasket Lastikli Spor Kasket
4.3
~~709 TL~~ 299 TL
SEPETE EKLE
Anasayfa
kategoriler
Favoriler
Bildirimler
Hesabim

Appendix I.: Gender Stereotype Signaling Content

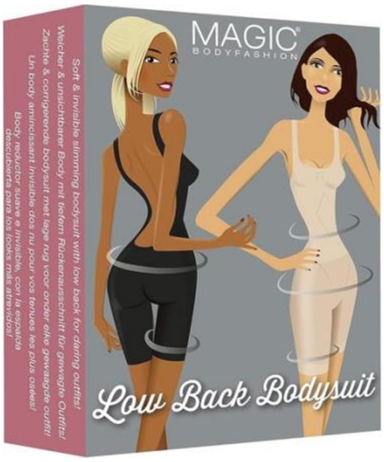
Recommender Type: Human - Male

Associative Recommender Group	Dissociative Recommender Group
Her zaman alışveriş yaptığınız büyük bir perakende satış mağazasına gittiğinizi düşünün. Geçmişte bu mağazanın kişisel bakım reyonundan deodorant, saç şekillendirici gibi çeşitli ürünler satın almıştınız. Şimdi de outdoor sporlarına yeni başlamış biri olarak soğuk, rüzgârlı ve nemin düşük olduğu yüksek irtifa bölgelerinde, cildin yanı sıra dudakların da kuruluğa ve çatlamaya daha yatkın olduğunu öğrendiğiniz için nemlendirici kremlerin yanı sıra **dudak nemlendiricisi** de aramaya başladınız. Dudak nemlendiricilerinin olduğu reyonda ürünleri incelerken bir satış danışmanı yanınıza yaklaşıyor ve ***"Bu ürünler de ilginizi çekebilir"*** diyerek, aşağıda ambalajlarını göreceğiniz ürünleri sunuyor. *(Lütfen görselleri dikkatlice inceleyin)*	Her zaman alışveriş yaptığınız büyük bir perakende satış mağazasına gittiğinizi düşünün. Geçmişte bu mağazanın kişisel bakım reyonundan roll-on, saç şekillendirici, nemlendirici gibi çeşitli ürünler satın almıştınız. Şimdi de sabah koşusuna yeni başlamış biri olarak soğuk ve rüzgârlı havalarda cildin yanı sıra dudaklar da kuruluğa ve çatlamaya daha yatkın olduğunu fark ettiğininiz için nemlendirici kremlerin ile **dudak nemlendiricisi** de aramaya başladınız. Dudak nemlendiricilerinin olduğu reyonda ürünleri incelerken bir satış danışmanı yanınıza yaklaşıyor ve ***"Dudak nemlendiricisi aradığınızı fark ettim. Bu ürünler de ilginizi çekebilir. Kore'nin en çok tercih edilen markaları"*** diyerek, aşağıda ambalajını ve / veya reklamını göreceğiniz ürünleri sunuyor. *(Lütfen görselleri dikkatlice inceleyin)*

	
Size özel sunulan bu ürünleri gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.	Size özel sunulan bu ürünleri gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.
Price Condition Bu aşamada satış temsilcisi, size önerdiği ürünlerin bazılarında **%50 indirimde** olduğunu hatırlıyor ve ekliyor *”Bu ürün şu anda bugüne özel %50 indirimde. Nivea Men Active Care **134 TL**'den* **67 TL***'ye inecek. “*	**Price Condition** Bu aşamada satış temsilcisi, size önerdiği ürünlerin bazılarında **%50 indirimde** olduğunu hatırlıyor ve ekliyor *”Bu ürün şu anda bugüne özel %50 indirimde. Vogule lips Man Balm kasada **209 TL**'den* **104,5 TL***'ye inecek. “*
	
Aşağıdaki ifadeleri ürünün **indirimli** fiyatını göz önünde bulundurarak değerlendirin.	Aşağıdaki ifadeleri ürünün **indirimli** fiyatını göz önünde bulundurarak değerlendirin.

Recommender Type: Human - Female

Associative Recommender Group	**Dissociative Recommender Group**
Her zaman alışveriş yaptığınız bir mağazaya gittiğinizi düşünün. Geçtiğimiz günlerde özel bir gün için aldığınız elbisenin daha güzel görünmesi adına korse arayışındasınız. İlginizi çeken modellerin bedenlerini ve renklerini inceliyor, almayı düşündüğünüz birkaç tanesini şimdilik elinizde tutuyorsunuz. Bu sırada satış danışmanı Ayşe, size ***"Bunlar da ilginizi çekebilir"*** diyerek, aşağıda paketini de göreceğiniz bir toparlayıcı korse modellerini sunuyor. *<u>(Lütfen görselleri dikkatlice inceleyin)</u>*	Her zaman alışveriş yaptığınız bir mağazaya gittiğinizi düşünün. Geçtiğimiz günlerde özel bir gün için aldığınız elbisenin daha güzel görünmesi adına korse arayışındasınız. İlginizi çeken modellerin bedenlerini ve renklerini inceliyor, almayı düşündüğünüz birkaç tanesini şimdilik elinizde tutuyorsunuz. Bu sırada satış danışmanı Ayşe, ***"Bu korselerin toparlayıcılığı daha fazladır hem kilolarınızı daha iyi gizler hem de 2 bedene kadar sıkılaştırarak sizi zayıf gösterir"*** diyerek, aşağıda göreceğiniz birkaç toparlayıcı korse modeli sunuyor. *<u>(Lütfen görselleri dikkatlice inceleyin)</u>*



Satış danışmanının sizi ve ihtiyaçlarınızı gözlemleyerek önerdiği ürünleri gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.

Satış danışmanının sizi ve ihtiyaçlarınızı gözlemleyerek önerdiği ürünleri gördüğünüzde hissettiklerinizi ve önerilenin sizde bıraktığı izlenimleri değerlendirerek bir sonraki bölümdeki soruları yanıtlamanızı rica ederiz.

Price Condition

Bu aşamada satış temsilcisi, size önerdiği ürünlerin bazılarında **%50 indirimde** olduğunu hatırlıyor ve ekliyor *"Bu ürün şu anda bugüne özel %50 indirimde. Nearly Nude seamless elbise korsenin fiyatı kasada* ***1100 TL'****den 5*__*95 TL*__*'ye inecek.*

Price Condition

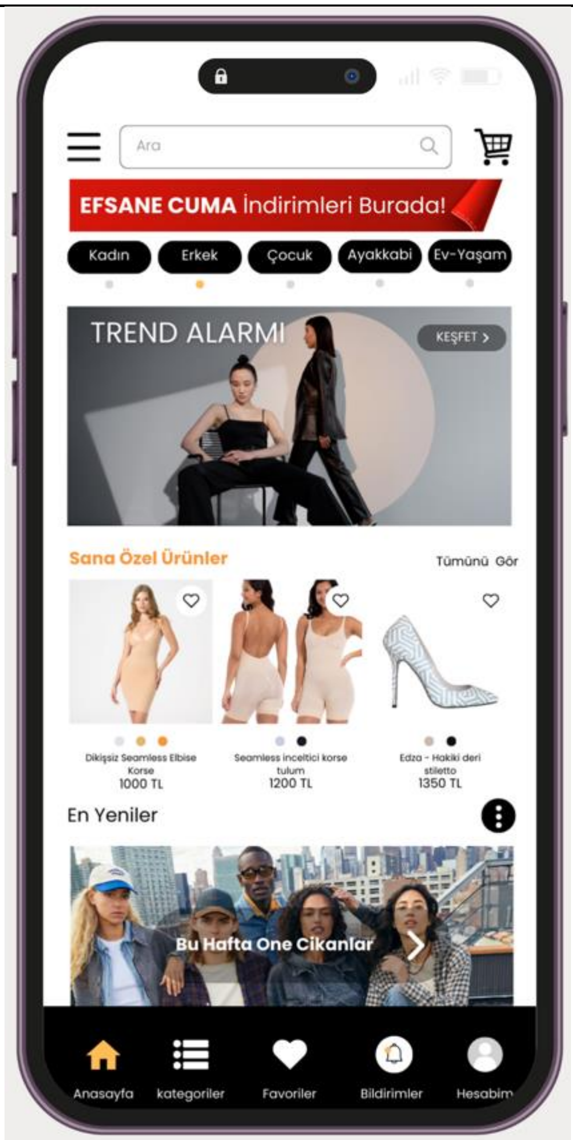
Bu aşamada satış temsilcisi, size önerdiği ürünlerde bugüne özel kasada geçerl**i %50 indirimde** olduğunu hatırlıyor ve ekliyor *"Bu ürünler şu anda bugün için %50 indirimde. Shapellx seamless elbise korsenin fiyatı kasada* ***990 TL'****den* __***495 TL'***__*ye, korse tulumun fiyatı* ***1200 TL***'den ***600 TL***'ye inecek.

Aşağıdaki ifadeleri ürünün **indirimli** fiyatını göz önünde bulundurarak değerlendirin.

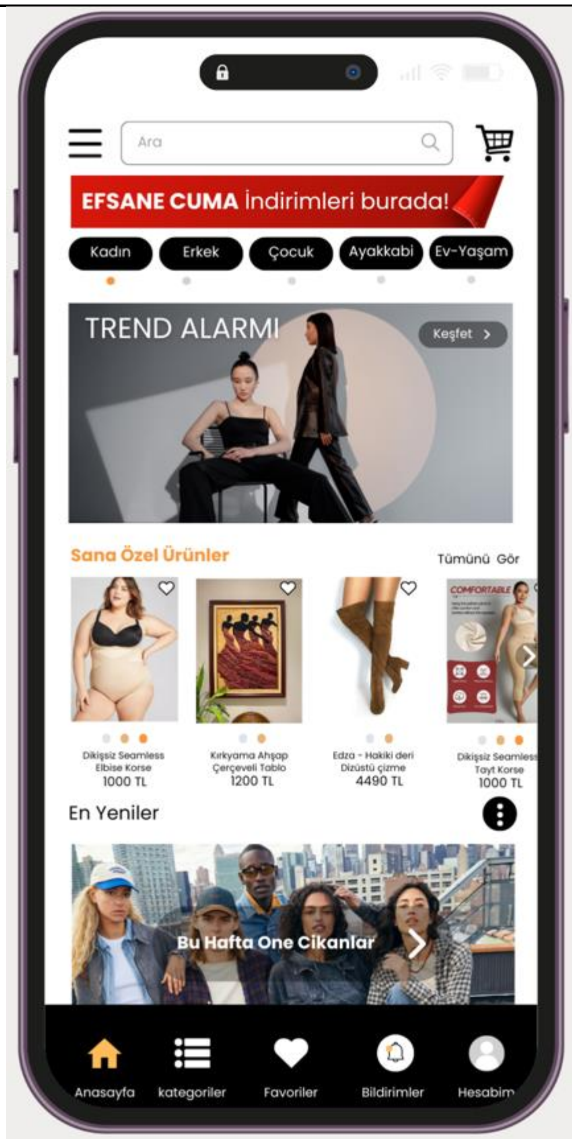
Aşağıdaki ifadeleri ürünün **indirimli** fiyatını göz önünde bulundurarak değerlendirin.

Recommender Type: AI - Female

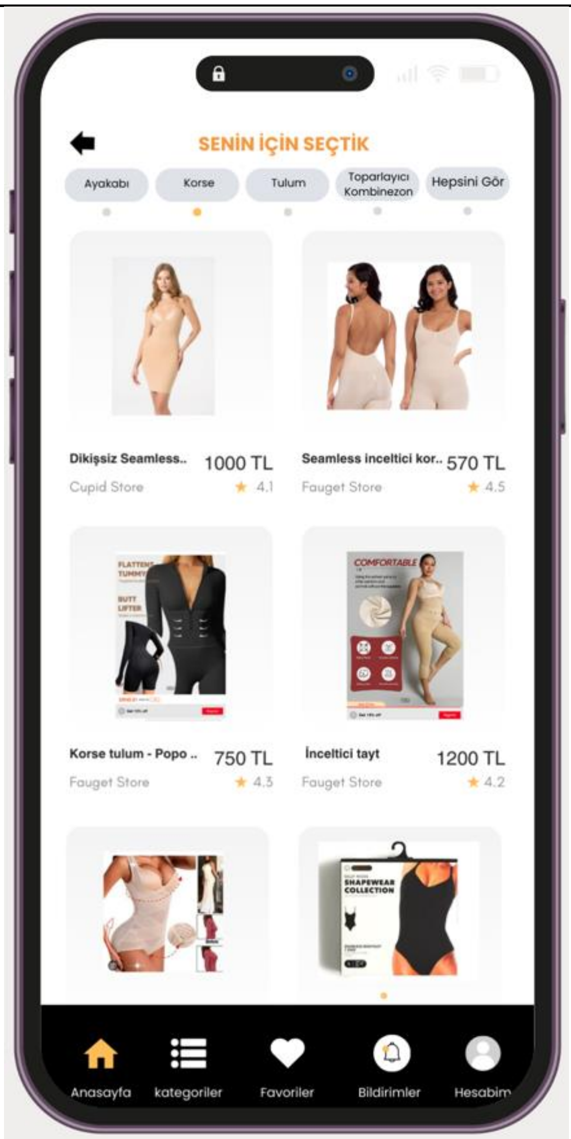
Associative Recommender Group	Dissociative Recommender Group
E-ticaret platformları *çoğunlukla, kullanıcı deneyimini* ***kişiselleştirmek*** *ve alışveriş süreçlerini hızlandırmak amacıyla* ***yapay zekâ tabanlı öneri sistemleri*** *kullanır. Bu sistemler, kullanıcıların* ***geçmişteki davranışlarını*** *(arama geçmişi, tıklamalar, satın alma işlemleri, favorilere eklenen ürünler vb.),* ***tercihlerini*** *(beden, renk, fiyat aralığı vb.) ve eğer kullanıcı tarafından verilmişse* ***demografik bilgilerini*** *(yaş, cinsiyet vb.)* ***analiz eder****. Bu analizlerden kalıplar ve ilişkiler çıkarmayı öğrenir ve elde edilen tüm bilgiler doğrultusunda* ***sınıflandırarak*** *kullanıcının ihtiyaç ve beğenilerine uygun* ***ürün veya içerik önerileri sunar.*** ***Kullanıcı davranışı değiştikçe****, sistem yeni davranışları* ***öğrenir*** *ve önerilerini buna göre* ***günceller****.* ***Ancak****, kullanıcı* ***davranışları değişmeden****,* **bu öneri çemberinin dışına çıkmak neredeyse imkansızdır.**	
Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün. Geçtiğimiz günlerde özel bir gün için aldığınız elbisenin daha hoş görünmesi için ***"toparlayıcı kombinezon," "elbise korse," "toparlayıcı elbise"*** gibi ürünler aramıştınız. Uygulamayı az önce tekrar açtığınızda, geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerin yer aldığı ***"Sana Özel Ürünler"*** başlığı altında, fit ve ince vücutlu bir modelin üzerinde sergilenen çeşitli korse ve şekillendirici ürünlerin bulunduğu aşağıdaki ekran ile karşılaşıyorsunuz. *(Lütfen görselleri dikkatlice inceleyin)*	Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün. Geçtiğimiz günlerde özel bir gün için aldığınız elbisenin daha hoş görünmesi için **"toparlayıcı kombinezon," "elbise korse," "toparlayıcı elbise"** gibi ürünler aramıştınız. Uygulamayı az önce tekrar açtığınızda, geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerin yer aldığı **"Sana Özel Ürünler"** başlığı altında, büyük beden bir modelin üzerinde sergilenen çeşitli korse ve şekillendirici ürünlerin bulunduğu aşağıdaki ekran ile karşılaşıyorsunuz. *(Lütfen görselleri dikkatlice inceleyin)*

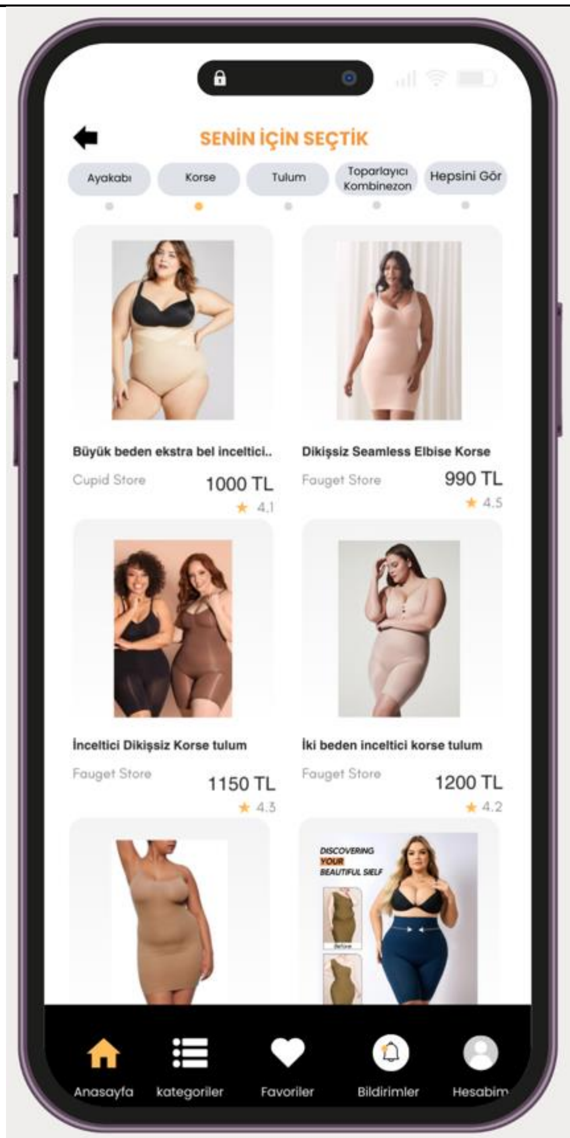


Tümünü gör butonuna tıkladığınızda **"SENİN İÇİN SEÇTİK"** bölümü altında korse kategorisinde aşağıdaki önerilerle karşılaşıyorsunuz.



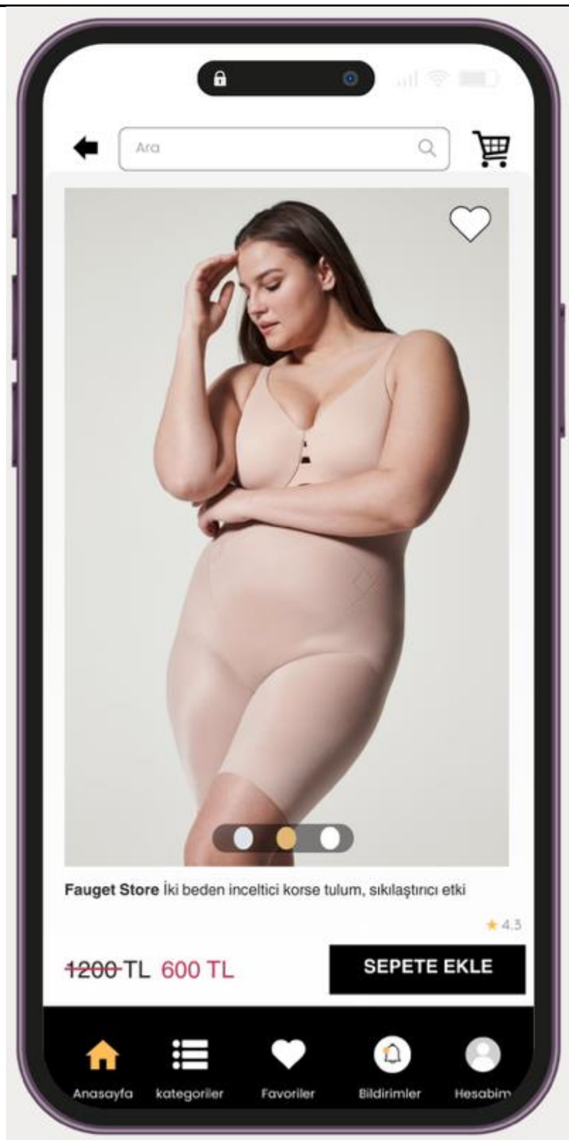
Tümünü gör butonuna tıkladığınızda **"SENİN İÇİN SEÇTİK"** bölümü altında korse kategorisinde aşağıdaki önerilerle karşılaşıyorsunuz.





Price Condition	**Price Condition**
Aynı gün içinde uygulamada gezerken, size önerilen ürünlerden aşağıdaki ürünün **%50 indirime** girdiğini fark ettiniz.	Aynı gün içinde uygulamada gezerken, size önerilen ürünlerden aşağıdaki ürünün **%50 indirime** girdiğini fark ettiniz.

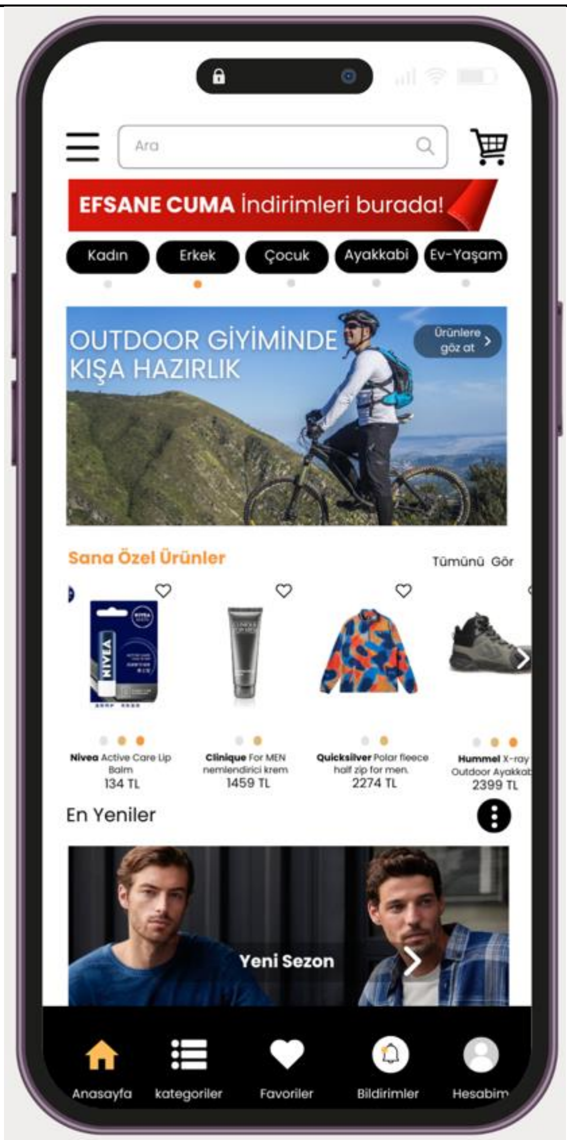

Ara
Cupid Store Dikişsiz seamless inceltici korse elbise
4.5
~~1000~~ TL 500 TL
SEPETE EKLE
Anasayfa
kategoriler
Favoriler
Bildirimler
Hesabım


Ara
Fauget Store İki beden inceltici korse tulum, sıkılaştırıcı etki
4.5
~~1200~~ TL 600 TL
SEPETE EKLE
Anasayfa
kategoriler
Favoriler
Bildirimler
Hesabım

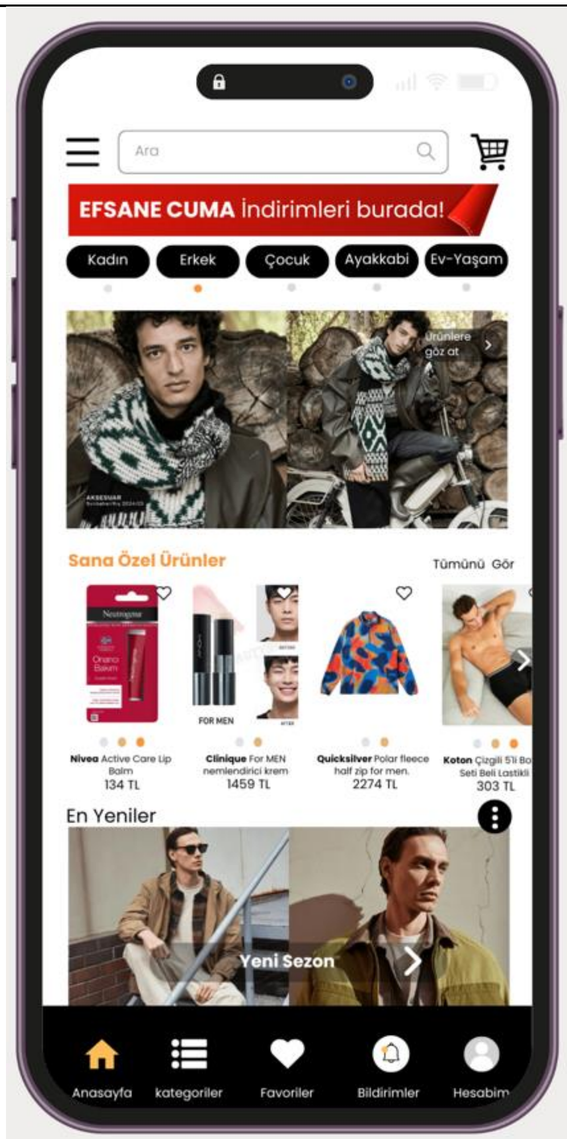
Recommender Type: AI - Male

<table>
<tr><th>Associative Recommender Group</th><th>Dissociative Recommender Group</th></tr>
<tr><td colspan="2">E-ticaret platformları çoğunlukla, kullanıcı deneyimini kişiselleştirmek ve alışveriş süreçlerini hızlandırmak amacıyla yapay zekâ tabanlı öneri sistemleri kullanır. Bu sistemler, kullanıcıların geçmişteki davranışlarını (arama geçmişi, tıklamalar, satın alma işlemleri, favorilere eklenen ürünler vb.), tercihlerini (beden, renk, fiyat aralığı vb.) ve eğer kullanıcı tarafından verilmişse demografik bilgilerini (yaş, cinsiyet vb.) analiz eder. Bu analizlerden kalıplar ve ilişkiler çıkarmayı öğrenir ve elde edilen tüm bilgiler doğrultusunda sınıflandırarak kullanıcının ihtiyaç ve beğenilerine uygun ürün veya içerik önerileri sunar.

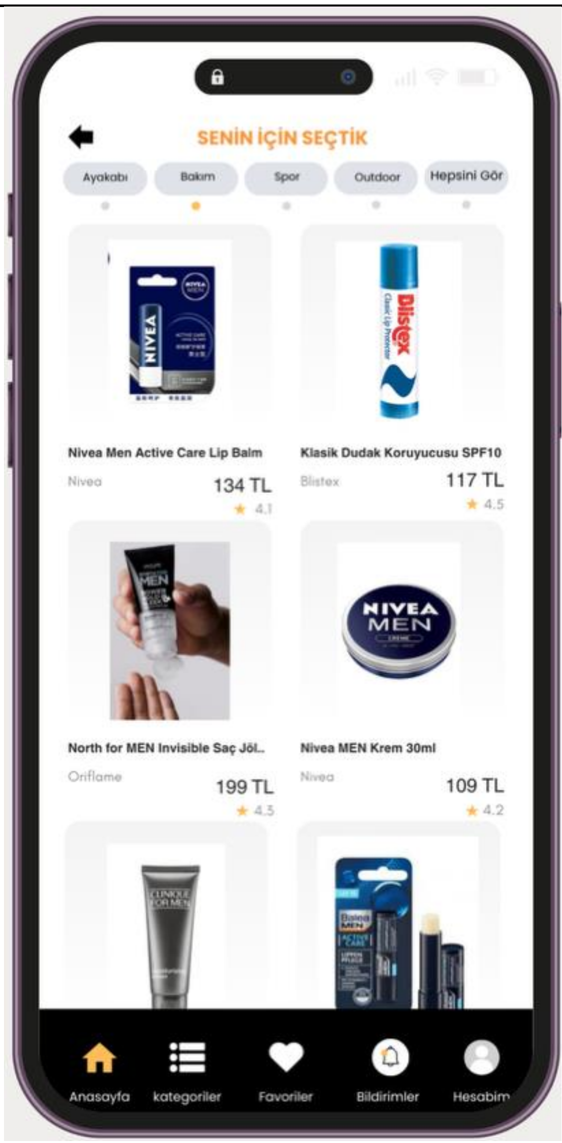
Kullanıcı davranışı değiştikçe, sistem yeni davranışları öğrenir ve önerilerini buna göre günceller. Ancak, kullanıcı davranışları değişmeden, bu öneri çemberinin dışına çıkmak neredeyse imkansızdır.</td></tr>
<tr><td>Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün.
Geçmişte "Erkek Bakım" kategorisinden deodorant, saç şekillendirici gibi çeşitli ürünler satın almıştınız. Şimdi de Outdoor sporlarına yeni başlamış biri olarak soğuk, rüzgârlı ve nemin düşük olduğu yüksek irtifa bölgelerinde, cildin yanı sıra dudaklar da kuruluğa ve çatlamaya daha yatkın olduğunu öğrendiğiniz için nemlendirici kremlerin yanı sıra dudak nemlendiricisi de aramaya başladınız.
Uygulamayı bugün açtığınızda, geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerin yer aldığı "Sana Özel Ürünler" başlığı altında, aşağıdaki ekran ile karşılaşıyorsunuz. (Lütfen görselleri dikkatlice inceleyin)</td><td>Şimdi sıklıkla kullandığınız (ürün araması yaptığınız, beğendiğiniz ürünleri favorilere eklediğiniz, alışveriş yaptığınız) bir e-ticaret uygulamasını açtığınızı düşünün.
Geçmişte "Erkek Bakım" kategorisinden roll on, saç şekillendirici, nemlendirici gibi çeşitli ürünler satın almıştınız. Şimdi de sabah koşusuna yeni başlamış biri olarak soğuk ve rüzgârlı havalarda cildin yanı sıra dudaklar da kuruluğa ve çatlamaya daha yatkın olduğunu fark ettiğininiz için nemlendirici kremlerin yanı sıra dudak nemlendiricisi de aramaya başladınız.
Uygulamayı bugün açtığınızda, geçmiş aramalarınıza dayanarak kişiselleştirilmiş önerilerin yer aldığı "Sana Özel Ürünler" başlığı altında, aşağıdaki ekran ile karşılaşıyorsunuz. (Lütfen görselleri dikkatlice inceleyin)</td></tr>
</table>

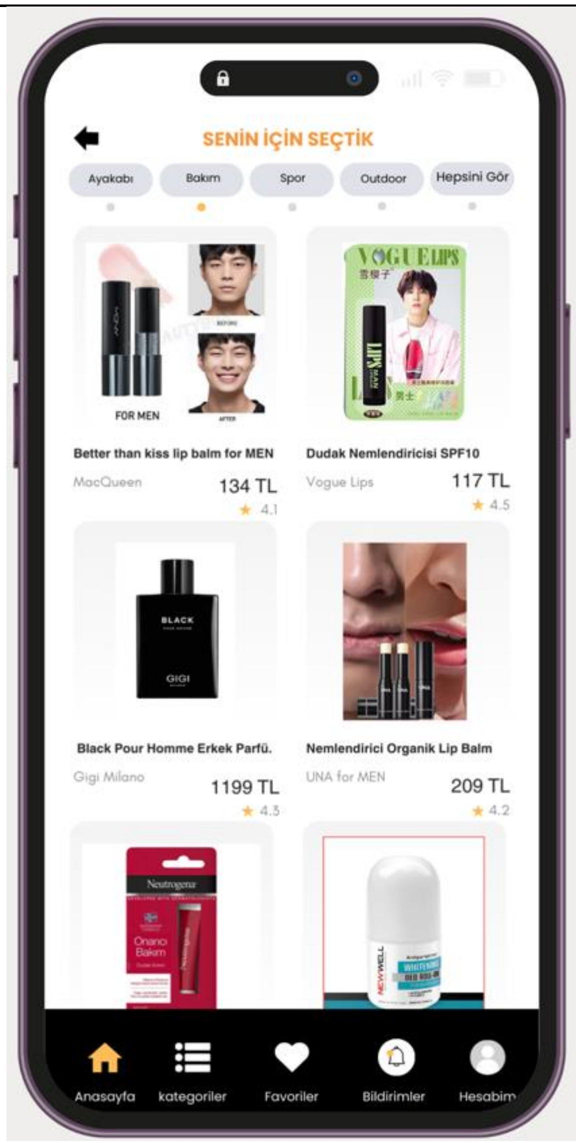


Tümünü gör butonuna tıkladığınızda **”SENİN İÇİN SEÇTİK”** bölümü altında “Bakım” kategorisinde aşağıdaki önerilerle karşılaşıyorsunuz.



Tümünü gör butonuna tıkladığınızda **”SENİN İÇİN SEÇTİK”** bölümü altında “Bakım” kategorisinde aşağıdaki önerilerle karşılaşıyorsunuz.





Price Condition Aynı gün içinde uygulamada gezerken, size önerilen ürünlerden aşağıdaki ürünün **%50 indirime** girdiğini fark ettiniz.	**Price Condition** Aynı gün içinde uygulamada gezerken, size önerilen ürünlerden aşağıdaki ürünün **%50 indirime** girdiğini fark ettiniz.


Ara
NIVEA
MEN
NIVEA
ACTIVE CARE
caring lip balm
妮维雅®护唇膏
男士型
SPF 20
水活滋润 不油腻
温和呵护 有效滋润
NIVEA Nivea Men Active Care Lip Balm
4.3
~~134~~ TL 67 TL
SEPETE EKLE
Anasayfa
kategoriler
Favoriler
Bildirimler
Hesabım


Ara
UNA
UNA
UNA
UNA for MEN Nemlendirici Organik Lip Balm
4.3
~~209~~ TL 104,5 TL
SEPETE EKLE
Anasayfa
kategoriler
Favoriler
Bildirimler
Hesabım