Master’s Thesis of Yun Ji Han

The Effect of Personalized versus Non-Personalized AI Recommendation System on Brand Evaluations: The Moderating Role of Consumption Type

개인화/비개인화 추천 시스템이 브랜드 평가에 미치는 영향: 소비 유형을 중심으로

August 2021

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Submitting a master's thesis of
Business Administration

August 2021

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Confirming the master's thesis written by
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August 2021

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Abstract

While previous literature on algorithm aversion and appreciation have directed their attention to comparing consumers' perceptions of AI recommendation agents against human agents, seldom were consumers' perceptions of different AI recommendation systems, despite their various techniques and proliferation in the real world, compared against each other. In such context, this study investigates how consumers' evaluations of online platform brands differ by the AI recommendation systems – personalized versus non-personalized – accentuated in brand messages. This study posits that the type of product sold in the online platform brand will influence the evaluations of different AI recommendation systems emphasized in brand messages. For hedonic consumption with multiple ideal points of preference, consumers would prefer to take recommendations from personalized AI recommendations which would meet their own specific ideal points over the non-personalized. Contrarily, for utilitarian consumptions that manifest high consensus in evaluation, there would be no difference in evaluations between personalized and non-personalized recommendation systems. This study further investigates the psychological mechanism of this effect: AI recommendation usefulness. Together, these results provide insights for online shopping platform brands in adopting effective AI recommendation systems for their product category and generating attractive brand messages regarding the recommendation system.

Keyword: Artificial Intelligence (AI), Recommendation Systems, Algorithms, Personalization, Hedonic Consumption, Utilitarian Consumption
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Table of Contents

Chapter 1. Introduction

The ongoing proliferation in the development and adoption of artificial intelligence (AI) have led marketing researchers to investigate consumers' perceptions and evaluations of AI under various consumption contexts (Longoni, Bonezzi, Morewedge 2019; Longoni and Cian 2020; Park and Kim 2019). Such research have primarily referred to studies on algorithm aversion and algorithm appreciation that reveal when people resist or prefer to employ algorithms over humans by comparing people' s lay beliefs about them (Dietvorst, Simmons, and Massey 2015, 2018, Castelo, Bos, and Lehmann 2019, Jussupow, Benbasat, and Heinzl 2020, Logg, Minson, and Moore 2019). The findings, overall, reveal that for tasks that are deemed uncertain or subjective in nature (Castelo, Bos, and Lehman 2019, Edwards, Duan, and Robbins 2000, Grove and Meehl 1996, Jarrahi 2018) or domains where affect and intuition are critical for decision-making (Longoni and Cian 2020), people favor taking advice from human agents over algorithms and AI. On the other hand, for tasks that are assumed to be complex or require objectivity through the use of big data or quantitative analyses (Bigras et al. 2018, Castelo, Bos, and Lehmann 2019, Jarrahi 2018), people prefer referring to algorithms and AI over human agents. Likewise, past literature on algorithm aversion and appreciation have primarily sought to find people' s perceptions of algorithms and AI through comparison with human agents.

Nevertheless, during this time where online shopping and un-tact delivery service thrives more than ever before, AI recommendation systems don' t just contend against men; they compete against each other. It' s been revealed that 46% of Korean female smartphone users in their 20s use mobile shopping applications, such as Ably, Brandi, and Zigzag, which provide a collection of shopping mall sites and their products in their platform (Heo 2021). Further, it' s been reported that major online shopping platforms including Musinsa(12 B won), Zigzag(8.5 B won), Ably(3.8 B won), Brandi(3 B won), W-Concept(3 B won) have generated a great amount of sales volume in the year 2020 despite the downturn of the global fashion industry under the pandemic crisis (Son 2021). The aforementioned companies are in a battle to win more downloads and purchases, using top rated celebrities and fetching catchphrases in their brand advertisement messages to captivate its target customers.

Such trends in retail and consumption suggests that algorithms and AIs no longer compete against men; they vie with each other. Therefore, it seems necessary to investigate when a specific type of AI recommendation system appeals more to consumers over another, and why. Many recommendation system techniques have been developed since the advent of the internet, which can be primarily categorized into personalized and non-personalized recommendation technique (Gabrani, Sabharwal and Singh 2017). While personalized recommendation systems provide recommendations based on the user's profile and preferences, non-personalized recommendation systems endorse products based on the popularity of items. While consumers' perceptions of AI have chiefly been speculated against that of human agents, rarely have consumers' perceptions on different AI recommendation systems that emphasize personalized and non-personalized recommendation techniques been investigated respectively.

Although consumers have lay belief that AI are unfit for recommending hedonic items rooted in affect and sensual pleasures (Longoni and Cian 2020) and domains where individual uniqueness should be taken into consideration (Longoni, Bonezzi, Morewedge 2019), AI recommendation services may be effective for hedonic consumption when personalization of the recommendation technique is emphasized, for consumers would believe the services would help meet their specific ideal points. On the other hand, for utilitarian products that demonstrate high consensus in product evaluation, there would be no preference for personalized recommendation. In brief, it is inferable that consumers would prefer personalized AI recommendation systems over non-personalized systems for hedonic product consumption, while no such effect would appear for utilitarian consumption. If such assumption proves to be correct, online shopping platform brands may not only adopt the particular type of recommendation technique proven to be more effective for the products and services they carry, but also accentuate such recommendation system techniques in their brand communication messages to maximize brand appeal.

Chapter 2. Theoretical Background

2.1. Perceptions on AI Algorithm

Since the advent of computational techniques, various algorithms have been developed with its terms evolving over time, the current trend of which is *artificial intelligence* (AI). Despite the lack of consensus in the definition of AI, AI is generally referred to as the capacity of a computational machine to learn from experiences, adapt to new inputs, and perform tasks that humans perform (Duan, Edwards, and Dwivedi 2019). Together with an expeditious advancement in big data technologies, AI is receiving an unprecedentedly large amount of attention from various domains, leading to its actual adoption in the medical fields, legal circles, education, entertainment, arts, and business (Duan, Edwards, and Dwivedi 2019).

Along with such evolvement, research on human perceptions about algorithms and AI have thrived primarily in comparison to human agents (Dietvorst, Simmons, and Massey 2015, 2018, Castelo, Bos, and Lehmann 2019, Jussupow, Benbasat, and Heinzl 2020, Logg, Minson, and Moore 2019). It' s been revealed that people have a propensity to prefer taking advice from human agents more than algorithms in making decisions, even if AIs are proven to be superior in that domain – a phenomenon coined as *algorithm aversion*

(Dietvorst, Simmons, and Masse 2015, 2018, Castelo, Bos, and Lehmann 2019). People have lay belief that algorithms are incapable of dealing with uncertainty, equivocality, and unstructured information (Edwards, Duan, and Robbins 2000, Grove and Meehl 1996, Jarrahi et al. 2018). Further, algorithms are trusted less for tasks that are presumed to be subjective in nature and require human affect (Castelo, Bos, and Lehmann 2019). In line with the findings, Longoni and Cian (2020) discovered that for hedonic consumption, consumers rely on AI recommendation agents less than humans, presuming they are incompetent in making affect and sensory driven decisions (Longoni and Cian 2020). Park and Kim (2019) also found that people resist taking advice from AIs and favor human recommendation agents for symbolic consumption, for they believe it’s exclusively human to long for symbolic meaning.

On the contrary, evidence show that people sometimes prefer to take recommendations from AI over humans (Logg, Minson, and Moore 2019). AI recommenders are perceived to be credible when it provides rich information that is easily accessible and requires less effort, leading to user’s higher adoption intention (Bigras et al. 2018). Furthermore, when tasks are framed as requiring quantitative analysis, consumers perceive the task to require objectivity, and trust the algorithm more through its perceived effectiveness (Castelo, Bos, and Lehmann 2019). Longoni and Cian (2020) additionally found that AI recommendation agents are favored more than human agents for utilitarian consumption, presumably because people believe they are more competent in making logical evaluations of the product and services.

Yet, despite the surge in research on comparison between algorithm/AI versus human agents, only few studies, to the best of the researcher’s knowledge, have been conducted to investigate people’s perceptions of different AI recommendation system techniques. In today’s online environment comprised of diversified online and mobile shopping platforms, AI no longer battle against men but contend with one another. Specifically, the upsurge in mobile fashion shopping applications and their escalating sales volume in the recent years in Korea (Son 2021) prove that people don' t resist AI recommendations for neither hedonic nor symbolic consumption, whose decision-making criteria are essentially rooted in human affect, intuition, and sensual pleasures. Moreover, the mobile shopping platforms are investing a great amount of money in developing and communicating effective recommendation systems that would appeal to their consumers, the most representative of which is Ably' s new brand message "Your personal AI shopping mate, Ably". Hence, consumers' perceptions on different types of recommendation systems and their techniques should be investigated thoroughly in the present research.

2.2. Recommendation System Techniques

Since the advent of computational systems, various types of recommendation system techniques have emerged and progressed. The recommendation techniques are most broadly classified into personalized and non-personalized recommendation techniques (Gabrani, Sabharwal, and Singh 2017). While personalized recommendation techniques provide recommendations for the user based on the user' s profile and preference, non-personalized AI recommendations rely simply on the popularity of items such as products ranked in top-N and provide the same recommendation for every user (Gabrani, Sabharwal, and Singh 2017, Poriya, Bhagat, Patel, and Sharma 2014). Personalized recommendation techniques comprise of content-based, collaborative filtering, and hybrid techniques based on how the algorithm functions to recommend specific products or services that fit the user' s preference. This research will focus specifically on the distinction between consumer' s perceptions of personalized versus non-personalized recommendation techniques accentuated in brand messages of online shopping platforms, for no study in marketing research has yet directly seen the contrast between them. Studies on personalization thus far have simply measured the perceived personalization level under different manipulations such as social presence (Choi, Lee, and Kim 2011).

As consumers resist AI in medical domains, believing it neglects individual uniqueness (Longoni, Bonezzi, and Morewedge 2019), it can be inferred that consumers would be willing to take recommendations from AI when the personalized feature is emphasized, in certain consumption contexts. Consumers may prefer personalized AI recommendation system when consuming hedonic goods, assuming that the system would help meet their specific tastes and preferences. However, this should not be the case for all product types. For utilitarian consumption which has tightly clustered ideal points, personalized recommendations may not be more preferable than non-personalized recommendation systems. Hence, the interaction effect of the recommendation system type and product category should be examined in detail.

2.3. Product Types and Preference Heterogeneity

Preference heterogeneity refers to the degree to which individual tastes and preferences of goods and services differ across consumers (Price, Feick and Higie 1989). High preference heterogeneity refers to substantial variation in preferences, low consensus in evaluation, and multiple ideal points regarding consumer tastes and preferences (Feick and Higie 1992). On the other hand, low preference heterogeneity implies little variation in preferences, high consensus in evaluation, and tightly clustered ideal points (Feick and Higie 1992).

Another conventional means to categorize product type is through hedonic and utilitarian products (Crowley, Spangenberg, and Hughes 1992, Voss, Spangenberg, and Grohmann 2003). Hedonic products relate more to consumers' multisensory fantasies, sensory attributes, and emotional arousal in consuming and using products (Hirschman and Holbrook 1982), and are generally associated with fun, excitement, and pleasure (Khan et al, 2004). Perfumes, chocolate, flowers, luxury watches, designer clothes, and sports cars are examples of hedonic products. Contrastively, utilitarian products are linked more to functionality, instrumentality, rationality, and tasks (Babin, Darden, and Griffin 1994). Products that fall into such category include detergents, home security systems, personal computers, and minivans (Dhar and Wertenbroch 2000).

Linking the two dimensions of product categories, Chu, Roh, and Park (2015) revealed that consumers view hedonic products as high preference heterogeneity products, while utilitarian products as low preference heterogeneity products. The findings indicate that hedonic products have multiple ideal points and have low consensus on evaluation among consumers, while utilitarian products have tightly clustered ideal points and exhibit high consensus on evaluation.

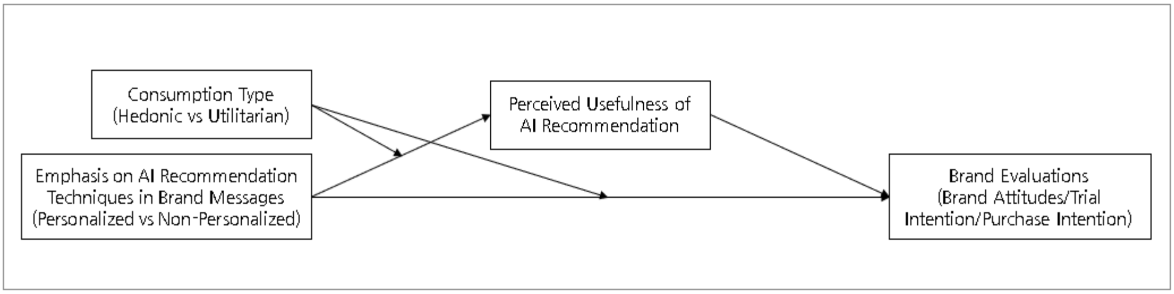
Therefore, it seems plausible to infer that consumers would perceive hedonic products with multiple ideal points as products they should actively search for in order to meet their precise ideal points. Correspondingly, personalized recommendation techniques that refer to the individual consumer's profile and preferences would be more preferable to consumers, for they can mitigate uncertainty of preference fit. On the other hand, such effect would not take place for utilitarian consumption with high consensus in evaluation, a domain where consumers don't look for products or services that fit their specific taste. Consumers may likewise prefer personalized recommendation over non-personalized recommendation exclusively for hedonic consumption.

2.4. Anticipated Usefulness of the AI Recommendation

Shopping online or through mobile entails great risk in that consumers are unable to experience the products before purchase (Bhatnagar, Misra, and Rao 2000, Luo, Ba, and Zhang 2012). Chu, Roh, and Park (2015) revealed that consumers prefer products with high rating dispersion over low rating dispersion for hedonic consumption through the mitigation of uncertainty about preference fit. Preference fit refers to the congruence between consumer preference and product attributes (Moon and Lee 2014).

Under such context, this study suggests a different psychological mechanism that would explain consumers' preference for brands with different recommendation systems: the perceived usefulness of the AI recommender system. Perceived usefulness refers to the degree to which consumers believe that using the recommendation service would enhance performance of finding and purchasing goods and services (Lee and Lee 2009). This study assumes that consumers' preference for personalized recommendation systems over non-personalized ones for hedonic consumption would be mediated by the perceived usefulness of the AI recommendation system.

Chapter 3. Research Model and Hypotheses



[Image 1] Research Model

H1a. For hedonic products, brand messages emphasizing personalized AI recommendation techniques would lead to higher evaluations of brand compared to those emphasizing non-personalized ones.

H1b. For utilitarian products, there would be no difference in evaluations between brands emphasizing personalized and non-personalized recommendation systems.

H2. The interaction effect of recommendation types and consumption type on brand evaluations would be mediated by the perceived usefulness of the AI recommendation.

Chapter 4. Pilot Study

The pilot test was conducted to examine the expected interaction between recommendation systems and consumption type. More specifically, the study hypothesized that personalized AI recommendation systems would be preferred over non- personalized ones only for hedonic consumption. Such assumption would not apply for utilitarian consumption, as consumers' evaluations for such products or services are perceived to be relatively unified.

4.1. Participants and Design

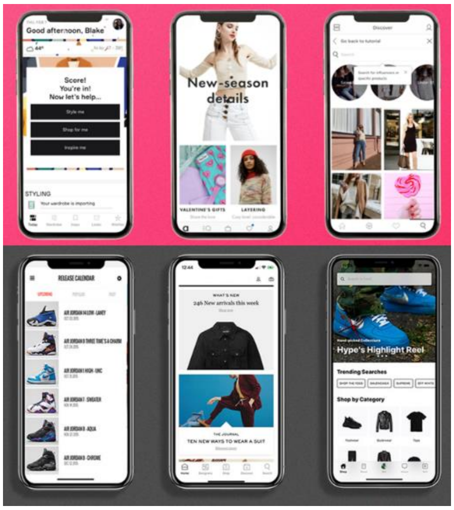
The study employed a 2 (Recommender Type: Personalized vs Non-personalized) × 2 (Product Type: Hedonic vs Utilitarian) between-subjects design, where participants were randomly assigned to one of the four conditions. A total of 160 participants recruited from MTurk participated in exchange for a small financial compensation. 23 participants with identical IP address, location, gender, and age were excluded from the study, leaving a total of 137 participants (Male 72%, M_{age}=35.41).

4.2. Stimuli and Procedure

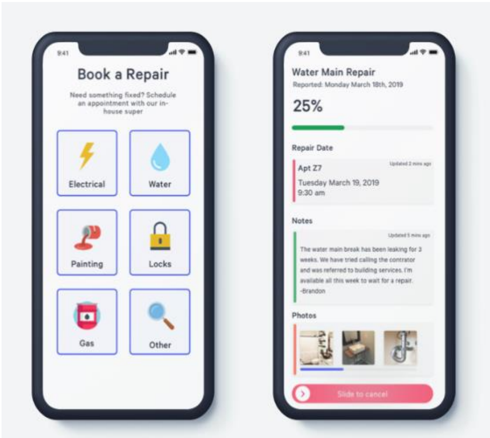
Participants were asked to view an advertisement message of either a fashion shopping app (hedonic consumption condition) or a home–repair service search app (utilitarian consumption condition), based on the condition they are in. Next, participants read a purported advertisement message of the application brand. The message emphasized different recommendation system types (personalized versus non–personalized) based on the conditions. The descriptions about the recommendation systems were primarily drawn from the definitions of each recommendation system from Gabrani, Sabharwal, and Singh (2017). The advertisement message of the electronics was as follows:

> Try our newly released *fashion shopping* [*home repair search*] app, which would recommend you *fashionable items that would bring fun, pleasure, and excitement to your daily lives* [*help accomplish your household tasks and fix problems you face at home*].
>
> Through our AI recommendation system, we recommend you fashion items based on the *analysis of your personal profile and unique preferences* [*most popular items that many other consumers have shown greatest satisfaction for in their ratings and reviews*].
>
> We have a list of more than 10,000 items that will *fit your specific taste* [*many other users prefer*], ready to be delivered to you right away!

Along with the advertisement text, a fictious image of an online shopping platform was provided to help participants visualize the consumption items [Image 3, 4].



[Image 2] Fashion Shopping Application



[Image 3] Home Repair Service Search Application

4.3. Measures

Participants first reported their attitudes, trial intention, and usage intention about the brand. For brand attitudes, they assessed services on four seven-point bipolar scale measurements: “bad/good”, “unpleasant/pleasant”, “unsatisfactory/satisfactory”, and “unfavorable/favorable”, retrieved from Chu, Roh, and Park (2015). For trial intention, participants answered two seven-point bipolar scale measurements comprised of “unlikely to try/likely to try” and “improbable to try/likely to try”, adapted from Chu, Roh, and Park (2015). For purchase intention, participants answered two seven-point bipolar scale measurements “unlikely to purchase products [service] from the brand/likely to purchase products from the brand” and “improbable to purchase products[service] from the brand/probable to purchase products[service] from the brand”, adapted from Chu, Roh, and Park (2015).

Regarding the manipulation check for product type, two seven-point bipolar items adapted from Chu, Roh, and Park (2015) were used: “related to amusement/related to practicality” and “helps divert me/promotes instrumental convenience”. As for the measure of preference heterogeneity, participants reported their perceptions about the items[services] through following scales: “Tastes are important in how people choose this product[service]”, “Preferences are important in how people choose this product[service]”, “For this product[service], individuals look for different things” (1= “not at all”, 7= “very much so”)

Additionally, twelve seven-point likert scale ancillary measures were used to measure product[service] involvement (O’Cass 2000, Mittal and Lee 1989), subjective knowledge (Flynn and Goldsmith 1999), consumption confidence (O’ Cass 2000), and prior mobile shopping experience (Smith, Menon, and Sivakumar 2005) ([Appendix A]).

4.4. Results

Manipulation Check

The manipulation check for consumption type (α=.76), using a one-way ANOVA revealed that fashion items related more closely to hedonic attributes than home repair services ($M_{fashion}$=5.12, $M_{home\ repair}$=5.74, $F(1, 135)$=8.56, p<0.01). However, the expected difference in preference heterogeneity (α=.70) did not turn out to be significant($M_{fashion}$=5.88 vs. $M_{home\ repair}$=5.77, $F(1, 135)$=.58,

p=>.1), indicating consumers expect preferences and tastes to differ for hedonic and utilitarian consumption on similar levels. The indifference may be due to home repair service having various sub categories that are either hedonic or utilitarain, whereas an example of low preference heterogeneity service in Feick and Higie (1992) – plumbing – is a single category that is highly utilitarian. Such result suggests that subsequent manipulations should accentuate the hedonic and utilitarian attributes more, by making a clearer distinction between consumption motive and advertisement message.

Brand Evaluation

For measuring brand evaluation, the average scores of brand attitudes, trial intentions, and purchase intentions (α=.94) were used. Contrary to the assumption, a 2(recommendation system type) × 2(consumption type) ANOVA on brand evaluations did not indicate a significant interaction effect (F(1, 133)=.5, p 6, >.1).

In order to find the reasons as to why the interaction effect did not turn out to be significant, a bootstrapping analysis was conducted using PROCESS model 3 with 5,000 bootstrap samples. Potential moderating effects of four ancillary variables on the main interaction effect on brand evaluations were tested. The ancillary variables included involvement(α=.88), knowledge(α=.91), consumption confidence(α=.88), and prior mobile shopping experience(α=.76).

The results revealed only a significant three-way interaction among the anticipated variables and prior mobile shopping experience. Subsequent Johnson Neyman floodlight analyses revealed that for those whose prior mobile shopping experience score was less than 4.48, a significant interaction between recommendation type and consumption type emerged. For participants with low mobile shopping experience (n=30), a 2(recommendation system type) × 2(consumption type) ANOVA on brand evaluations revealed a significant interaction effect (F (1,22)=4.78, p =.04), when involvement, knowledge, and interaction was controlled. Further simple contrasts revealed the propensity of low mobile shopping experience participants to prefer personalized recommendation systems over non−personalized recommendation systems when consuming hedonic goods ($M_{pesonalized}$ =5.33 vs. $M_{non-personalzied}$ =4.09, t (13)=1.95, p =.07). Despite such results, the findings lack robustness in that the sample size was small, reducing the power of the study.

4.5. Discussion

The pilot study revealed a potential three−way interaction among recommendation system type, consumption type, and prior mobile shopping experience. The interaction effect between recommendation type and consumption type may emerge solely for consumers with low prior mobile shopping experience, which should be investigated more thoroughly in the following main experiment.

Despite the finding of a potential moderating variable, the pilot study has many limitations. First and foremost, the anticipated interaction effect and the simple contrast showed up only with an additional moderator variable. Second, the study lacks reliability and robustness in that the number of low mobile shopping experience participants were too small (n=30) and the simple contrast was only marginally significant (p <.1). Lastly, the expected effect of consumption type on preference heterogeneity did not emerge, which means that the manipulation was not representative enough of the utilitarian consumption.

The successive main experiment should hence reveal an interaction and simple contrast to improve the robustness of the findings, while taking into consideration the potential moderator prior online[mobile] shopping experience. To do so, a stronger manipulation of consumption type should be conducted. The main experiment thus manipulates the consumption type distinctive of the recommendation system manipulation, manipulating consumption type prior to recommendation systems. Additionally, the consumption motive will be manipulated using the same product category, so to eliminate potential confounds and establish the causal link more vividly.

Chapter 5. Main Study

The objectives of the main study was fourfold. The first objective was to test the hypothesized main effect and simple contrasts which were accepted only conditionally in the pilot study. Secondly, the study tested the mediating role of the perceived usefulness of AI recommendation system in preference for personalized recommendation systems over non-personalized ones for hedonic consumption. In addition, in order to manifest the causality more clearly, the study manipulated consumption type through assigning different consumption motives under the same product category. Lastly, the study underscored the features of each consumption motive more concretely compared to the pilot study in order for them to be more representative of each consumption type.

5.1 Participants and Design

The study employed a 2 (Recommender Type: Personalized vs. Non-personalized) × 2 (Product Type: Hedonic vs. Utilitarian) between-subjects design, where participants were randomly assigned to one of the four conditions. A total of 159 participants (Male 76%, M_{age}=34.67) recruited from MTurk participated in the study, in exchange for a small financial compensation.

5.2 Stimuli and Procedure

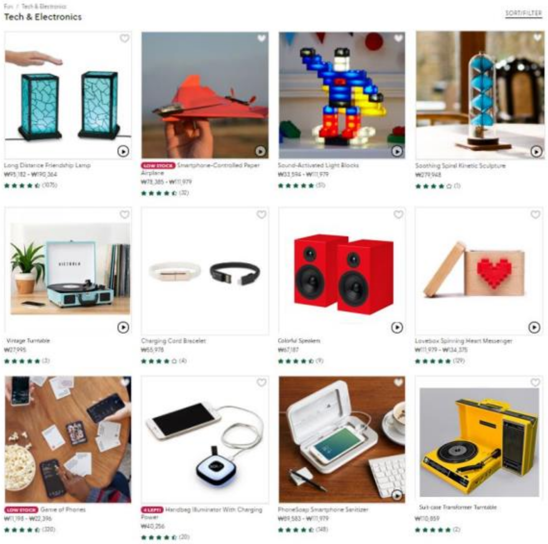
Depending on the condition, participants were asked to imagine that they have either set up a new room specifically for leisure[study] and fun[work]. They had to look for electronic devices to fill in that room, which would help bring more pleasure to their free time [promote work efficiency and accomplish tasks effectively]. Then, they were asked to think about two to three electronic items that would bring pleasure and fun to their new room [enhance work efficiency].

They further imagined while searching for the devices, they arrived at an online shopping platform specializing in electronics for home décor and entertainment [office electronics]. They were once again reminded of the features of the products they are looking for through a quote retrieved from Longoni and Cian (2020), which goes "Remember, you are looking for electronic devices that is fun[functional], enjoyable[useful], and speaks to your emotions[rationality]".

Next, participants read an advertisement message they purportedly encountered in the online shopping platform. The message emphasized different types of recommendation systems and were similar to the ones in the pilot study. The advertisement message of the electronics was as follows:

> Try our electronic shopping platform, specializing in electronics for *home décor and entertainment* [*electronics*]. Through our *personalized* [*popularity-based*] AI recommendation system, we recommend you items you are searching for based on *the analysis of your personal profile and unique preferences* [*the best-selling items that many consumers have bought and shown satisfaction for*]. We have a list of more than 10,000 *decor and entertainment items that will suit your specific taste* [*office items that consumers most commonly prefer*], ready to be delivered to you right away!

Just like the pilot study, a fictitious image of an electronics online shopping platform was provided to remind participants of the consumption motives and the corresponding items once again.



[Image 4] Online Shopping Platform for Hedonic Consumption

[Image 5] Online Shopping Platform for Utilitarian Consumption

5.3 Measures

The measures of brand evaluations were comprised of attitudes toward the online shopping platform brand, brand trial intention, and purchase intention through the brand. The measurements were identical to the first study but differed in that this time we used nine-point likert scale measurements instead of seven-point scales.

For the hypothesized mediation variable, participants indicated the usefulness of the AI recommender system through six nine-point scale likert scale measurements, retrieved and adapted from retrieved from Chu, Roh, and Park (2015) and Lee and Lee (2009). The measures included "Using this service enables me to find goods more quickly", "Using this service enables me to find goods more easily", "Using this service is helpful to purchase goods", "I think the purchase decision based on this shopping platform would lead to better outcomes", "I can see the benefits in the AI recommendation systems that help make purchase decisions", and "I find this shopping platform useful in purchasing goods I want" (1=strongly disagree, 9=strongly agree),

Regarding the manipulation check for product type, four nine-point bipolar items adapted from Chu, Roh, and Park (2015) were used. Among them, two were identical to the pilot study. Additional measurements included the following: the electronic items I am looking for is "beneficial to my leisure/enhances work efficiency" and "emotional/logical". As for the manipulation check for preference homogeneity, participants reported their perceptions on three nine-point likert scales retrieved from Chu, Roh, and Park (2015): "Tastes are important in how people shoes this product(service)", "Preferences are important in how people choose product(service)", "For this product(service), individuals look for different things" (1= "not at all", 9= "very much so"). To check the recommendation type, one nine-point bipolar scale was used to assess how the AI recommendation system provide recommendations to its users 1 = "based on the user's unique preference" and 9= "based on the popularity of the item".

Finally, participants completed the ancillary measures and potential confounds which were identical to the pilot study. In addition, they evaluated the perceived threat to future use (Lee and Lee 2009) and need for uniqueness (Tian, Bearden, and Hunter 2001) ([Appendix A]).

5.4 Results

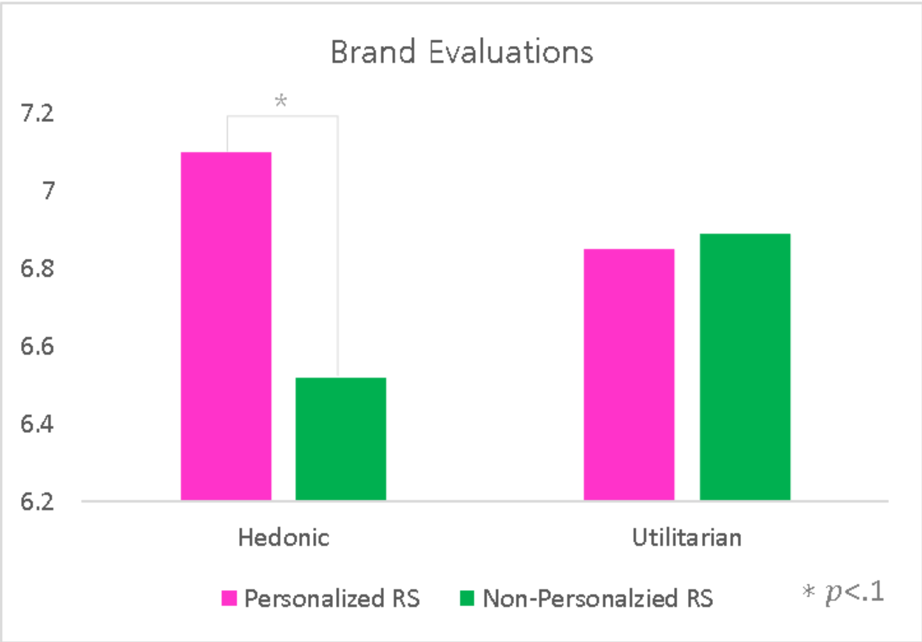
Manipulation Check

A 2 (recommendation type) × 2 (consumption type) ANOVA on manipulation check for consumption type (α=.92) indicated that electronics for leisure and fun associated more closely with hedonic qualities compared to electronics for work and study ($M_{leisure}$=5.48 vs. M_{study}=7.03, F(1,157)=25.01, p<.01). Yet, the same ANOVA on preference heterogeneity (α=.73) once again failed to show the expected difference between the consumption types. Contrary to assumption, results reveal that participants were influenced more by the advertisement message underscoring the brand' s specific recommendation system in perceiving the importance of preferences and tastes in consuming electronic goods ($M_{Personalized}$=6.91 vs. $M_{non-personalized}$=6.50, (F(1,157)=2.86, p=.09). Lastly, the same ANOVA was conducted once more on the manipulation check measure for recommendation system type. The results indicated that the manipulation for recommendation type was successful ($M_{Personalized}$=5.51 vs. $M_{non-personalized}$=6.49, F (1,157)=6.30, p=.01).

Brand Evaluations

A 2 (recommendation type) × 2 (consumption type) ANOVA on brand evaluations (α=.91) revealed a marginally significant interaction between recommendation type and consumption type (F (1,151)=2.89, p =.09), when controlling for product involvement(α=.76), product knowledge(α=.77), consumption confidence (α=.75), and prior online shopping experience ([Image 5]). Further, simple contrast within the hedonic consumption domain revealed that evaluations on brands using personalized recommendation systems marked higher scores compared to those using non-personalized ones ($M_{hedonic-personalized}$=6.89 vs. $M_{non-personalized}$=6.37, F(1,73)=3.95, p=.05), when controlling for the same four variables. On the contrary, additional contrast analysis indicated that for utilitarian consumption, the evaluations for brands emphasizing distinct recommendation systems did not differ ($M_{utilitarian-personalized}$=7.07 vs. $M_{non-personalized}$=7.03, $F(1,73)$=.03, p=.86), under the same control condition.

Likewise, this study demonstrated the presumed interaction and simple contrast effect, albeit being marginally significant and controlling for confound variables. Emphasis on personalized recommendation systems in brand messages appeal only for hedonic consumption contexts, and not for utilitarian consumption domains. If so, questions arise on why consumers prefer personalized AI recommendation systems over non-personalized systems only for hedonic consumption domains. Thus, the study further investigated the psychological mechanism of this effect and tested whether the presumed variable, usefulness of AI recommendation system, in fact mediated this effect.



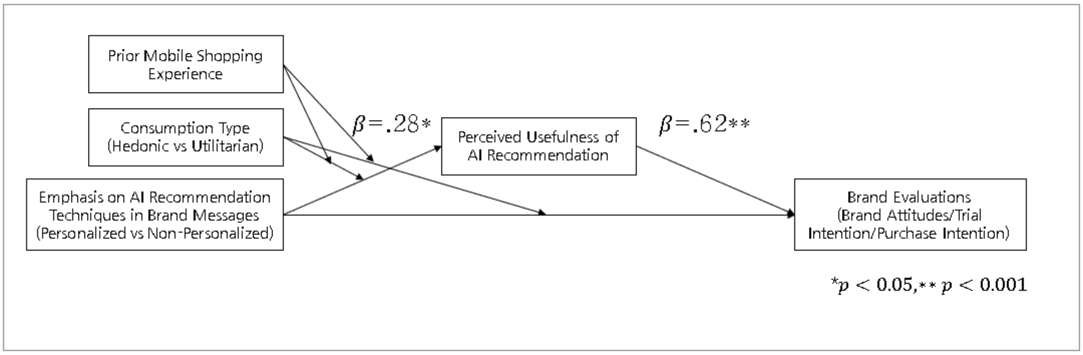
[Image5] Interaction Effect of Recommendation Systems and Consumption Type on Brand Evaluations

Perceived Usefulness of AI recommender System

A 2(recommendation type) × 2 (consumption type) ANOVA on perceived usefulness of AI recommender system did not reveal the presumed interaction effect, despite controlling for the confound variables (F (1,151)=1,961 p =.16). Consequently, further bootstrapping analysis to reveal the moderated mediation effect was unnecessary.

Since the findings of the pilot study indicated that prior experience in online[mobile] shopping moderated the interaction of recommendation type and consumption type on brand evaluations, we inferred that a similar effect would apply for perceived usefulness of AI recommendation as well. We therefore conducted bootstrapping analysis with PROCESS model 12 (Preacher and Hayes 2004), to identify a potential mediating effect of perceived usefulness under different levels of prior online[mobile] shopping experience.

The results revealed a significant three-way interaction among recommendation type, consumption type, and prior shopping experience on perceived usefulness of the AI recommendation (β=.28, t=−2.36, p=.02). Additionally, the effect of usefulness of the AI recommendation on brand evaluation also turned out to be significant (β=.62, t=10.42, p<.01) ([Image6]). The results further showed that an indirect effect was significant only for those with low prior shopping experience in hedonic consumption condition, whose prior shopping experience scores are one standard deviation below the mean (5.56; 95 percent confidence interval [CI]=−.9134, −0.01). As the direct effect for all conditions are revealed to be insignificant (all ps>0.05), it can be said that the perceived usefulness of AI recommendation fully mediates the effect of recommendation type and consumption type on brand evaluations, only when low experienced online[mobile] shoppers search for hedonic goods or services.



[Image 6] Moderated Mediation Effect

Low Online/Mobile Shopping Experience Consumers

Additional Johnson-Neyman analysis revealed that the interaction effect of recommendation system and consumption type to be statistically significant for those whose prior shopping experience is lower than 6.71 ([CI] does not include zero), a finding which corresponds to the pilot study.

In other words, the interaction effect obtains greater significance for those whose prior online[mobile] shopping experience is relatively low. For those whose online[mobile] shopping experience is relatively low, the endorsement of personalized recommendation systems would be more appealing than non-personalized recommendation systems in the hedonic consumption domain, through perceived usefulness of the AI recommendation system. However, such effect may not hold true for those who are highly experienced in online[mobile] shopping. Though the underlying psychological mechanism of experienced online[mobile] shopping consumers remains to be secluded, future studies may uncover the effect.

5.5 Discussion

The main study revealed the hypothesized interaction and simple contrast effects, albeit on marginally significant levels. According to the findings of this study, consumers have a propensity to prefer personalized recommendations over non-personalized recommendations only for hedonic consumptions. The preference for personalized recommendation services did not turn out to be significant for utilitarian consumptions.

The study further disclosed the underlying psychological mechanism for the interaction effect, albeit only for consumers with low online[mobile] shopping experiences. For consumers with low prior online[mobile] shopping experience, the perceived usefulness of the AI recommender system fully mediated the effect of recommendation system and product type on online platform brand evaluations. As the experienced online[mobile] shopper's evaluations for different recommender types and its underlying psychological mechanism remains to be undisclosed, future research may delve deeper into the shopping behaviors and AI perceptions of experienced online[mobile] shoppers.

Chapter 6. General Discussion

Theoretical Implications

The present research is one of the first to investigate consumer's attitudes and behavioral intentions toward different types of recommendation systems in marketing research. Despite the surge of research on perceptions toward Artificial Intelligence (AI) in algorithm aversion and appreciation literature, only a few studies to the best of the researcher's knowledge have explored consumer's differing attitudes toward different types of AI recommendation techniques.

Furthermore, the findings of this research provide insights into ways algorithm aversion can be mitigated. While previous literature on algorithm aversion reveal that consumers reject AI recommendations for consumption domains associated with emotions, sensual pleasures, and fantasies (Longoni and Cian 2020), the present finding discovered that consumers have a propensity to favor AI recommendation techniques for hedonic consumption, when its personalized recommendation technique is emphasized in brand messages. That is, consumers prefer personalized recommendation techniques over non-personalized recommendations only for hedonic consumption domains. Thus, the implementation and promotion of personalized recommendation techniques should help alleviate consumers' distaste for algorithm recommendation for hedonic consumption. For utilitarian consumption, there was no significant difference between evaluations for personalized and non-personalized recommendation systems, just as hypothesized.

The study further found a mediating variable – perceived usefulness of AI recommendation system – for consumers with low prior online/mobile shopping experience in search for hedonic goods and services. That is, consumers with low prior online shopping experience favor personalized recommendation systems for hedonic consumption, perceiving the system to be useful in finding and purchasing goods. The finding, to some extent, concurs with the hypothesis that the perceived usefulness of the AI recommendation system would mediate the preference for personalized AI recommendation systems over non-personalized for hedonic consumption.

Managerial Implications

The study provides fruitful insights to marketing practitioners of online platform brands in developing services and communicating their brand messages. For brands that carry hedonic goods such as luxury apparel, designer furniture, sports cars, or fragrances, establishing and promoting personalized AI recommendation techniques would help enhance their brand evaluations. Consumers' aversion towards algorithm recommendations for hedonic consumption would be mollified through marketing communications underscoring the system's personalization features.

Stressing personalized recommendation techniques would also help hedonic consumption related brands acquire a new consumer segment – online[mobile] shopping novices – as they prefer personalized recommendations over non-personalized, believing they are more useful in searching for hedonic goods and services. On the other hand, the promotion of the recommendation system techniques would not appeal for utilitarian goods and services, which include utility vehicles, office supplies, electronic goods, and plumbing services. Marketing managers of online/mobile shopping platforms should likewise endorse the adoption of personalized AI recommendation systems to their brands and accentuate such features in their brand messages only when their products and services fall under the hedonic category.

Limitations and Future Research Directions

The question remains on why highly experienced online shoppers do not prefer personalized recommendation systems for hedonic consumption through the expected mediating variable: perceived usefulness of the recommendation system. Do experienced online shoppers find all recommendation systems to be unhelpful in all online shopping contexts? Are experienced online consumers merely confident in themselves for browsing the web and searching for goods that fit their exact tastes and find the recommendation system nagging? Or is there another psychological mechanism that would explain their preference for personalized recommendation systems over non-personalized recommendation for hedonic consumption? Future research may further probe on the attitudes and perceptions heavy online shoppers have about different types of online recommendation systems.

Further, the psychological mechanism behind the lack of difference in evaluations toward personalized and non-personalized recommendation systems for utilitarian products and services remain to be undisclosed. This study had hypothesized that consumers would show no preference for personalized recommendation systems over non−personalized systems for utilitarian consumption domain, due to the lay belief that consumers would exhibit high consensus in evaluating utilitarian products and services. Contrary to expectations, however, a significant difference in perceived preference heterogeneity did not emerge between the hedonic versus utilitarian categories in all studies. Future research may strengthen the utilitarian manipulation and verify whether consumers actually do perceive utilitarian products and services to manifest high consensus in evaluation and tightly clustered ideal points.

Bibliography

Babin, Barry J., William R. Darden, and Mitch Griffi (1994), "Work and/or Fun: Measuring Hedonic and Utilitarian Shopping Value," *Journal of Consumer Research*, 20(4), 644−56.

Bhatnagar, Amit, Misra, Sanjog, Raghav H. Rao (2000). "On Risk, Convenience, and Internet Shopping Behavior," *Communications of the ACM*, 43:11, 98−105.

Bigras, Emilie, Marc−Antoine Jutras, Sylvain Sénécal, Pierre−Majorique Léger, Chrystel Black, Nicolas Robitaille, Karine Grande, and Christian Hudon (2018), "In AI We Trust: Characteristics Influencing Assortment Planners' Perceptions Of AI Based Recommendation Agents", in *HCIBGO 2018, LNCS*, Montréal: Springer International Publishing AG, Springer Nature 2018, 3−16.

Castelo, Noah, Maarten W. Bos, and Donald R. Lehmann (2019), "Task−Dependent Algorithm Aversion," *Journal of Marketing Research*, 56(5), 809–25.

Choi, Jaewon, Hong Joo Lee, and Yong Cheol Kim (2011), "The Influence of Social Presence on Customer Intention to Reuse Online Recommender Systems: The Roles of Personalization and Product Type", *International Journal of Electronic Commerce*, 16(1), 129−54.

Chu, Wujin, Minjung Roh, and Kiwan Park (2015), "The Effect of the Dispersion of Review Ratings on Evaluations of Hedonic Versus Utilitarian Products," *International Journal of Electronic Commerce*, 19(2), 95−125.

Crowley, Ayn E. Eric R. Spangenberg, and Kevin R. Hughes (1992), "Measuring the Hedonic and Utilitarian Dimensions of Attitudes toward Product Categories," *Marketing Letters*, 3, 239−49.

Dhar, Ravi and Klaus Wertenbroch (2000), "Consumer Choice between Hedonic and Utilitarian Goods", *Journal of Marketing Research*, 37(1), 60−71.

Dietvorst, Berkeley J., Joseph P. Simmons, and Cade Massey (2015), “Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err,” *Journal of Experimental Psychology*, 144 (1), 114–26.

_________ (2016), “Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them,” *Management Science*, 64 (3), 1155–70.

Duan, Yanqing, John J. Edwards, and Yogesh K Dwivedi (2019), “Artificial Intelligence for Decision Making in the Era of Big Data–Evolution, Challenges and Research Agenda,” *International Journal of Information Management*, 48, 63–71.

Edwards, John S., Yanqing Duan, and Paul C. Robins (2000), “An Analysis of Expert Systems for Business Decision Making at Different Levels and in Different Roles,” *European Journal of Information Systems*, 9(1), 36–46.

Feick, Lawrence F and Higie, Robin A. (1992). “The Effects of Preference Heterogeneity and Source Characteristics on Ad Processing and Judgements about Endorsers,” *Journal of Advertising*, 21(2), 9–24.

Flynn, Leisa Reinecke and Ronald E. Goldsmith (1999), “A Short, Reliable Measure of Subjective Knowledge”, *Journal of Business Research*, 46(1), 57–66.

Gabrani, Goldie, Sangeeta Sabharwal, and Viomesh K. Singh (2017), “Artificial Intelligence Based Recommender Systems: A Survey”, *ICACDS 2016, Communications in Computer and Information Science,* Vol. 721, eds. Singh M., Gupta P., Tyagi V., Sharma A., Ören T., Grosky W. SG: Advances in Computing and Data Sciences, 50–9.

Grove, William M. and Paul E. Meehl (1996), “Comparative Efficiency of Informal (Subjective, Impressionistic) and Formal (Mechanical, Algorithmic) Prediction Procedures: The Clinical– Statistical Controversy,” *Psychology, Public Policy, and Law*, 2 (2), 293–323.

Heo, Kyungjin (2021), “다양한 패션 쇼핑몰을 한 번에…모음앱

인기몰이", *Sky Daily*, May 13th.
Hirschman, Elizabeth C. and Morris B. Holbrook (1982), "Hedonic Consumption: Emerging Concepts, Methods and Propositions," *Journal of Marketing*, 46(3), 92−101.
Jarrahi, Mohammad Hossein (2018), "Artificial Intelligence and the Future of Work: Human−AI Symbiosis in Organizational Decision Making," *Business Horizons*, 61(4), 577–86.
Jussupow, Ekaterina, Izak Benbasat, and Armin Heinzl (2020), "Why Are We Averse Towards Algorithms? A Comprehensive Literature Review on Algorithm Aversion", in *Proceedings of the 28th European Conference on Information Systems (ECIS)*, 1−16.
Khan Uzma, Ravi Dhar, and Klaus Wertenbroch (2004), "A Behavioral Decision Theory Perspective on Hedonic and Utilitarian Choice", Chapter in *Inside Consumption: Frontiers of Research on Consumer Motives, Goals, and Desires*, eds. S. Ratneshwar & David Glen Mick.
Lee, Gyudong and Won Jun Lee (2009), "Psychological Reactance to Online Recommendation Services", *Information & Management*, 46 (8), 448−452.
Logg, Jennifer M., Julia Minson, and Dan A. Moore (2019), "Algorithm Appreciation: People Prefer Algorithmic to Human Judgment," *Organizational Behavior and Human Decision Processes*, 151, 90–103.
Longoni, Chiara, Andrea Bonezzi, and Carey K. Morewedge (2019), "Resistance to Medical Artificial Intelligence," *Journal of Consumer Research*, 46 (4), 629–50.
Longoni, Chiara and Luca Cian (2020), "Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The 'Word−of−Machine' Effect," *Journal of Marketing*, 1−18.
Luo, Jifeng, Sulin Ba, and Han Zhang (2012), "The Effectiveness of Online Shopping Characteristics and Well−Designed Websites on Satisfaction," *MIS Quarterly*, 36(4), 1131−44.
Mittal Banwari, Myung−Soo Lee (1989), "A Causal Model of

Consumer Involvement”, *Journal of Economic Psychology*, 10(3), 363–389.

Moon, Heekang and Hyun-Hwa Lee (2014), “Consumers' Preference Fit and Ability to Express Preferences in the Use of Online Mass Customization”, *Journal of Research in Interactive Marketing*, 8(2), 124–43.

O’Cass A (2000), “An Assessment of Consumers Product, Purchase Decision, Advertising and Consumption Involvement in Fashion Clothing,” *Journal of Economic Psychology*, 21 (5), 2000, 545–576.

Park, Kiwan and Yaeri Kim (2019) ,"Man Versus Ai: Resisting Technology in Symbolic Consumption", in NA - *Advances in Consumer Research,* Vol. 47, eds. Rajesh Bagchi, Lauren Block, and Leonard Lee, Duluth, MN : Association for Consumer Research, 804–806.

Poriya Anil, Tanvi Bhagat, Neev Patel, and Rekha Sharma (2014), “Non-Personalized Recommender Systems and Userbased Collaborative Recommender Systems”, *International Journal of Applied Information Systems,* 6(9), 22-7.

Preacher, Kristopher .J. and Andrew F. Hayes (2004), “SPSS and SAS Procedures for Estimating Indirect Effects in Simple Mediation Models,” *Behavior Research Methods, Instruments, & Computers*, 36, 717–731.

Price, Linda L., Lawrence F. Feick, and Robin A. Higie (1989). “Preference Heterogeneity and Coorientation as Determinants of Perceived Informational Influence,” *Journal of Business Research*, 19(3), 227–242.

Smith Donnavieve, Satya Menon, K. Sivakumar (2005), “Online Peer and Editorial Recommendations, Trust, and Choice in Virtual Markets”, *Journal of Interactive Marketing*, 19(3), 15–37.

Son, Jungbin (2021), “MZ세대 공략 성공…무섭게 크는 온라인 패션 플랫폼”, *Newsis*, May 14.

Tian, Kelly T., William O. Bearden, Gary L. Hunter (2001), “Consumers' Need for Uniqueness: Scale Development and Validation," *Journal of Consumer Research*, 28(1), 50–66.

Voss, Kevin E., Eric R. Spangenberg, and Bianca Grohmann (2003), "Measuring the Hedonic and Utilitarian Dimensions of Consumer Attitude", *Journal of Marketing Research*, 40(3), 310−20.

Appendix

[Appendix A]

Construct	Measurements
Involvement	1) ~ products[services] are important to me. 2) I have a strong interest in ~. 3) I am very much involved with ~.
Subjective Knowledge	1) I am very familiar with ~. 2) feel I know a lot about ~. 3) I am an experienced user of ~. 4) I would classify myself as an expert on ~.
Consumption Confidence	1) I am confident I would choose the right brand[service] for ~. 2) When considering ~ for purchase I am confident that I would make the right choice. 3) I have confidence in my ability to make the best choice concerning ~.
Online Shopping Experience	1) Prior to your participation in this study, how would you rate your level of experience in terms on online[mobile] shopping? 2) Prior to your participation in this study, how would you rate your level of experience in terms on online[mobile] booking? 3) Prior to your participation in this study, how would you rate your level of experience in terms on online[mobile] shopping[booking], specifically for ~?
Threat to Future Use	1) The service will bother me in using the website. 2) The service will interfere in my using the website.
Consumer's Need for uniqueness	1) I avoid products or brands that have already been accepted and purchased by the average consumer. 2) When products or brands I like become extremely popular, I lose interest in them. 3) I collect unusual products as a way of telling people that I'm different.

국문 초록

최근 마케팅 연구에서는 특정 소비 영역에서 인간 추천 대비 인공지능 추천에 대한 소비자들의 반감을 나타내는 알고리즘 적대감(Algorithm Aversion) 현상이 밝혀졌다. 그러나 인공지능 추천 시스템의 유형별 소비자 인식을 살펴본 연구는 아직까지 드문 상황이다. 이에 본 연구는 브랜드 메시지가 소구하는 추천 시스템 유형(개인화 추천 vs. 비개인화 추천)에 대한 소비자 인식이 소비 유형(쾌락 소비 vs. 유용 소비)별로 다르다는 것을 입증한다. 이상 점(ideal point)이 다양한 쾌락 소비의 경우, 소비자들은 자신의 고유한 이상 점을 만족시키는 상품 및 서비스를 추천해줄 개인화 추천 시스템을 선호할 것이다. 반면 제품에 대한 평가 일치도가 높은 유용 소비의 경우, 개인화 추천 시스템과 상품 인기도에 따른 추천을 제공하는 비개인화 추천 시스템 간 소비자 선호도에는 차이가 없을 것이다. 이러한 효과는 인지된 인공지능 추천 시스템 유용성이라는 심리적 기재에 의해 매개될 것이다. 종합적으로, 본 연구 결과는 브랜드가 취급하는 품목이나 개인의 소비 동기에 따라 개인화 대 비개인화 추천 시스템에 대한 선호가 달라진다는 것을 입증, 브랜드 매니저들이 브랜드에 적합한 추천 시스템을 도입하고 효과적인 브랜드 메시지를 구상하는 데 유용한 시사점을 제공할 것이다.

키워드: 인공지능(AI), 추천 시스템, 알고리즘, 개인화 추천, 쾌락소비, 유용소비
학번: 2019-28093