

Effect of AI Recommendation System on the Consumer Preference Structure in e-Commerce: Based on Two types of Preference

Namjun CHA*, Hosoo CHO*, Sangman LEE*, Junseok HWANG*

* Technology Management, Economics and Policy Program, Seoul National University,
1 Gwanak-ro, Gwanak-gu, Seoul 08826, Korea
chanj86@snu.ac.kr, lakecho@snu.ac.kr, puresoul@snu.ac.kr, junhwang@snu.ac.kr

Abstract— The goal of this research is figuring out AI recommendation effects on consumer's preference by their types. In this study, two types of consumer's preference are considered including 'category preference' and 'attribute preference', and also types of goods are divided into manufactured products and contents by their properties such as tangibility. Two laboratory experiments will be conducted to test four hypotheses. We expect that this study gives an important message for the effective use of AI recommendation system in e-commerce platforms.

Keywords— e-commerce, online market, preference, AI recommendation, marketing

I. INTRODUCTION

As artificial intelligence (AI) technologies have developed rapidly in recent years, they are utilized in a variety of industries actively. Web-based service such as search portals, shopping portals and media platforms is one of those industries. They maximize users' convenience and experience through a recommendation system—a type of artificial intelligence.

There are scholars who warn about harmful effects of recommendation system on the information and media industry, such as filter bubble and echo chamber. According to these theories, the use of a recommendation system has risk of reducing diversity of the society and polarizing opinions. However, in this study, we will focus on only e-commercial services such as web shopping and media content services, which are positive use cases of recommendation systems.

The goal of this research is figuring out effects of AI recommendation system on user(customer)'s preference. In marketing area, research on the effect of design, display, advertising of goods on consumer's preferences has been conducted [7]-[10]. There has also been research on the effect of AI recommendation systems on revenues for companies [5], [6]. To the best of our knowledge, this paper is the first one that investigates the effects of AI recommendation system on consumer's preference. Based on the result, managerial implications will be provided in e-commerce industry. We expect this research to give considerable message on strategical use of AI recommendation.

II. LITERATURE REVIEW

A. Recommendation System

In this study, we focus on the AI recommendation system. A recommendation system produces a set of recommendations using two methods: collaborative filtering and content-based filtering [1], [4]. Collaborative filtering builds a filter using a user's behaviour history such as clicks, purchase, ratings as well as similar decisions made by other users. This filter is then used to make a list of items that the user may have an interest in [2]. Content-based filtering builds a filter analysing a series of discrete properties of an item that user chose to recommend other items with similar characteristics [3]. These methods can operate independently, simultaneously, or combined [4].

B. Recommendation System and User Behaviour

Some researchers warned that the use of recommendation system can negatively affect user's perception. Eli pariser said a website algorithm selectively guesses what information a user would like to see based on its algorithm on the basis of information about the user, such as location, past click-behaviour and search history [17]. As a result, users become separated from information that disagrees with their opinions, isolating themselves in their own ideological bubbles. Many scholars have confirmed the existence of filter bubbles by recommendation system usage through various research methodologies.

Echo chamber is a similar concept, and the result is same, but it is different on its view [18]. Cass Sunstein said it happens due to the psychological motivation that people only consume similar items to their ideologies actively and voluntarily. The reason why this phenomenon has recently been revealed is that there are more options in media than in the past.

However, recommendation system is a convenient and useful tool. It relieves user's efforts to find new information and recommends items even they did not know. Thus, we need to understand people's behaviour when they are exposed to AI recommendation system.

C. Consumer Preference and Behaviour

Consumer preference theory shows how a consumer ranks a collection of goods or services or prefers one collection over another, over assumptions that consumer ranks goods or services by the amount of satisfaction, or utility, afforded [11]-[12]. Consumers tend to consume more products or brands they prefer according to this theory.

There is a study that observed the capture effect of pioneering product, which means when the 'ambiguity' exists, consumers prefer the products with attribute with which they are more familiar [13]. It is because in the early stages of a market, consumers know very little about the importance of attributes or their ideal combinations. Though, numerous studies raised the intriguing possibility that marketing strategy such as continuous exposure and advertisement actually influence consumer preferences [7]-[10].

D. Properties of products and contents

In this research, we analyse goods by dividing them into manufactured product and content, because there are clear differences in terms of properties between the manufactured product and the content as well as tangibility.

The typical characteristics of content are experience goods and credence goods [14]-[16]. Generally, contents are difficult to assess the value of a good before using it and to assess its quality accurately even after using the product. We call manufactured products as "products" in this study for the convenience.

Also, we consider two types of consumer's preference including 'category preference' which refers to consumer's preferred category of goods and 'attribute preference' which means a preferred combination of attributes' of goods.

The categories of manufactured products and contents are different. For manufactured products, we follow the categories that online shopping malls classified such as clothes, electronics, furniture. For contents, we follow the categories that online media platform classified such as game, sport, news. Also, the attributes of manufactured products and contents are different. Manufactured products have color, size, length as their attributes, but contents have duration, type of content such as image, text, and video as their attributes.

TABLE 1. TYPE, CATEGORY AND ATTRIBUTE OF GOODS

	Goods	
	Products	Contents
Category	Clothes / Electronics / Furniture...	Game / Sport / News...
Attribute	Color / Size / Length...	Image / Text / Video / Duration...

III. HYPOTHESIS

The goal of this research is figuring out AI recommendation effects on consumer's preference by the types of products. Based on the literature review, we assumed that recommendation system will have different effects on consumer preference depending on whether the target is a product or a content.

According to the literature, preference hardly changes for the attributes of product which formed in the past [13]. Because increasing firm's revenues exploiting the recommendation algorithm is a fundamental reason for using it, we can say the recommendation algorithm encourages consumers to purchase products from different categories of the related attributes learned by AI recommendation system [5].

For the contents, it is an experience and credence goods, consumers explore opinions and assessments around them to reduce uncertainty of the content's quality [14]-[16]. Thus, consumer's preference on contents is strongly influenced by the information that recommendation system provides.

To sum up, the hypotheses are as follows:

A. Product

recommendation system will increase preference of consumers for products in different categories(H1a), but will not increase their preferences for products of different attributes(H1b).

- H1a: The recommendation system will increase preference of consumers for products in different categories.
- H2a: The recommendation system will not increase preference of consumers for products in different attributes.

B. Contents

Conversely, recommendation system will not increase preference of consumers for contents in different categories(H2a), but will increase their preferences for contents of different attributes(H2b).

- H2a: The recommendation system will not increase preference of consumers for contents in different categories.
- H2b: The recommendation system will increase preference of consumers for contents in different attributes.

IV. METHODOLOGY

We will adopt laboratory experiment to capture the preference change. Laboratory experiment is able to exactly control extraneous and independent variable due to direct observation and face-to-face condition. In the present study, selection behavior should be observed as clear as possible, because we assume that the choice of participant refers to his or her preferences. Also, we will survey the reason of his behavior during the experiment for clear motivation to prove whether participant's behavior is impulsive or not.

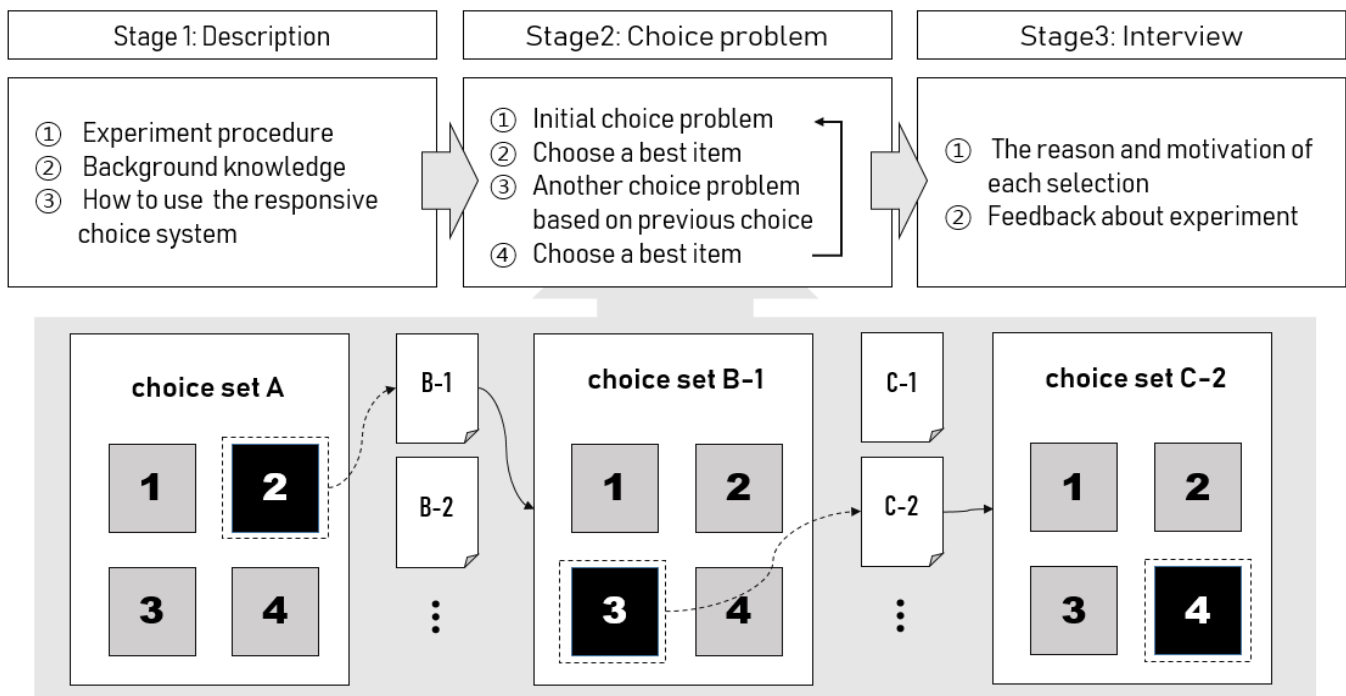


Figure 1. Description of the experiment design

Experiment consists of three stage. At the first stage, detail description of experiment procedure will be provided to each participant. This explanation will include crucial information to implement our experiment.

The second stage is actually observing the selection behavior of participants. In this step, we will collect not only the result of selection but also its reason. This stage will be repeated until the participant finishes all decision problems that we prepared. Also, the decision problems, which refer to buying process in online store, will give the environment involving customized advertisement based on their previous purchases(choices). To give similar experience with actual online shopping behavior, we will provide a responsive choice system made by html.

Finally, at the third stage, we will conduct an interview with the participants. From this interview, we expect to collect data about the motivation or reason of each choice.

Each choice set includes 4 items which consist of random combination of product properties and the properties vary by its product category. The participants may choose an item based on both the category preference and product attributes and then following choice set will be combined previously selected category or attributes with new ones. The participants will experience a system which is similar to the online AI recommendation in terms of a perspective that the system brings product recommendations considering both their previous choice and the other's choice.

From this experiment, two results will be drawn. One is related to the preference changes in product category, and another is the result of preference change of product attributes. The goal of present study is figuring out the impact of AI recommendation system on consumer's preference involving

category and attribute. So, we can decide whether our hypothesis is accepted or rejected by using these results.

V. CONCLUDING REMARKS

We expect that this study brings an important message for the effective use of AI recommendation system in e-commerce platforms. Especially, our paper can give considerable messages on strategical use of AI recommendation, such as suggesting criteria that determine effective AI recommendation strategy to the provider of e-commerce platform in various context. Also, we expect this research to be utilized and advanced in academic area such as marketing, management and computer science.

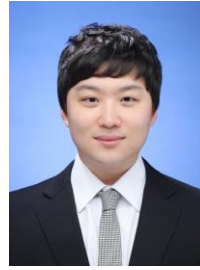
REFERENCES

- [1] Jafarkarimi, H., Sim, A. T. H., & Saadatdoost, R. A naive recommendation model for large databases. *International Journal of Information and Education Technology*, 2(3), 216, 2012.
- [2] Schafer, J. B., Frankowski, D., Herlocker, J., & Sen, S. Collaborative filtering recommender systems. In *The adaptive web* (pp. 291-324). Springer, Berlin, Heidelberg, 2007.
- [3] Pazzani, M. J. A framework for collaborative, content-based and demographic filtering. *Artificial intelligence review*, 13(5-6), 393-408, 1999.
- [4] Koren, Y., Bell, R., & Volinsky, C. Matrix factorization techniques for recommender systems. *Computer*, (8), 30-37, 2009.
- [5] Schafer, J. B., Konstan, J., & Riedl, J. Recommender systems in e-commerce. In *Proceedings of the 1st ACM conference on Electronic commerce* (pp. 158-166). ACM., November, 1999.
- [6] Chen, H., Chiang, R. H., & Storey, V. C. Business intelligence and analytics: from big data to big impact. *MIS quarterly*, 1165-1188, 2012.
- [7] Bloch, P. H. Seeking the ideal form: Product design and consumer response. *The Journal of Marketing*, 16-29, 1995.

- [8] Phillips, B. J., McQuarrie, E. F., & Griffin, W. G. How visual brand identity shapes consumer response. *Psychology & Marketing*, 31(3), 225-236, 2014.
- [9] Park, C. W., & Young, S. M. Consumer response to television commercials: The impact of involvement and background music on brand attitude formation. *Journal of marketing research*, 11-24, 1986.
- [10] Lee, D., Hosanagar, K., & Nair, H. S. Advertising content and consumer engagement on social media: evidence from Facebook. *Management Science*, 2018.
- [11] Lancaster, K. J. A new approach to consumer theory. *Journal of political economy*, 74(2), 132-157, 1966.
- [12] Thaler, R. Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, 1(1), 39-60, 1980.
- [13] Carpenter, G. S., & Nakamoto, K. Consumer preference formation and pioneering advantage. *Journal of Marketing research*, 285-298, 1989.
- [14] Wan, Y., Nakayama, M., & Sutcliffe, N. The impact of age and shopping experiences on the classification of search, experience, and credence goods in online shopping. *Information Systems and e-Business Management*, 10(1), 135-148, 2012
- [15] Throsby, D. Determining the value of cultural goods: How much (or how little) does contingent valuation tell us?. *Journal of cultural economics*, 27(3-4), 275-285, 2003
- [16] Burke, A. E. The demand for vinyl LPs 1975–1988. *Journal of Cultural Economics*, 18(1), 41-64, 1994
- [17] Pariser, E. *The filter bubble: What the Internet is hiding from you*. Penguin UK, 2011
- [18] Sunstein, C. R. *Echo chambers: Bush v. Gore, impeachment, and beyond*. Princeton, NJ: Princeton University Press, 2001



Namjun Cha is a Ph.D candidate of technology management, economics and policy program(TEMPEP) in SNU, South Korea. He has studied about the diffusion and acceptance of IoT services and the optimization of government assessment system of Korea. Recently, he focuses on the collective intelligence in AI supported environment.



artificial intelligence, and policy for SMEs.

Hosoo Cho received the B.S degree from Kobe University, Kobe, Japan in 2013, in electrical and electronic engineering with Korea–Japan joint government scholarship program. He received M.S. degree from Seoul National University in 2016, in electrical and computer engineering majored in Internet of Things and communication protocols. He is currently working towards the Ph.D. degree at SNU with technology management, economics and policy program(TEMPEP). His research interests include social impact of convergence technology,



Sangman Lee is a Ph.D candidate of technology management, economics and policy program(TEMPEP) in SNU, South Korea. He has been interested in the ICT capability and its effect on social welfare. In addition, he is recently attempting to figure out how AI technology affects the labor market structure.



Junseok Hwang is a full professor at TEMEP in SNU. He holds BS in Mathematics from Yonsei University, MS in Telecommunications from University of Colorado, and Ph. D in Information Science and Telecommunications from University of Pittsburgh. He is specialized in telecommunications and IT policy.