Application of FEA consumer needs model in real practice, e-commerce: chatbot for fashion product recommendation

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Introduction

With the development of digital technology, e-commerce companies have adopted chatbot services to influence consumers' purchase intentions by providing helpful information and engaging experiences (Chung et al., 2020). However, adapting these methods to fashion product recommendations poses challenges due to the abundance of options. In clothing and textile studies, consumer needs theory provides factors that explain consumer motivations for choosing a particular design. Lamb and Kallal (1992) suggested the FEA consumer needs model by categorizing consumer needs for apparel design based on functional, expressive, and aesthetic attributes. Therefore, the study aims to configure a taxonomy of e-commerce fashion product attributes that can fill the gap between chatbot technology and consumer needs theory for fashion product recommendations. The research steps were as follows. First, we theoretically reviewed the current technology of the chatbot recommender system in e-commerce. Second, we applied consumer needs theory to configure the taxonomy of fashion product attributes for the conversational recommender system (CRS). Third, we evaluated the CRS framework using an experimental scenario and validated the effectiveness of consumer needs attributes in e-commerce fashion product recommendations.

Literature review

Chatbot recommender system in e-commerce

In the e-commerce big data environment, product recommender systems have become essential for digital consumers' product searches. Traditional recommender systems typically predict user preferences based on historical data, such as click history and item ratings (Wang et al., 2021). While proven to be a success, there is an intrinsic limitation in that these traditional methods find it difficult to capture the dynamic preferences of consumers. The recently emerging CRS has overcome this limitation. CRS enables traditional recommender systems to learn users' explicit preferences by asking questions through interactive conversations (Lei et al., 2020a). However, these methods are inefficient in fashion e-commerce because there are too many options. An intuitive solution is to leverage the attribute information of products, which can quickly narrow down the candidate product by understanding user intention (Zhang et al., 2021). Thereby in this study, we adopt advanced CRS and apply consumer needs theory to enhance recommendation performance for fashion products in e-commerce.

Taxonomy of fashion product attributes

Taxonomy is the science of naming, describing, and classifying items, and the terms, along with typology and framework, are sometimes used interchangeably (Wand et al., 1995). The research approach to creating a taxonomy is based on the design science research paradigm, which aims to address new knowledge about artificial objects that are designed to meet certain goals and provide utility to their users (Simon, 1988). In the chatbot recommender system, each attribute of the taxonomy is applied as a keyword to an interactive conversation and becomes a guide to finding the right product. Based on the theoretical review, the study applied consumer needs theory to configure the CRS's taxonomy of fashion product attributes.

Methods

To configure the taxonomy of fashion products, we first started with the conceptual approach and then examined empirical cases to see how they fit with the conceptualization (Bailey, 1984). We applied the FEA consumer needs model and product design elements (shape, color, material, and detail) to classify fundamental categories and attributes. Then, we derive the value of each functional, expressive, and aesthetic attribute by comparing the relative information extracted from e-commerce. After creating a taxonomy development, we need to demonstrate its efficacy by applying it to specific domains (Nickerson et al., 2013). Thus, we selected the domain of e-commerce and applied the taxonomy to the experimental scenario to examine the effect.

Dataset

We collected data from Coupang (https://www.coupang.com), the largest e-commerce platform in South Korea that can track user purchase history. We limited the data to products in the women's fashion categories. Over 20,000 product profiles (e.g., title, brand, price) and 500,000 user records (e.g., user identifiers, review text, satisfaction reports) were collected. Using graph information, the search space and overhead of the algorithm for the CRS Framework can be significantly reduced (Lei et al., 2020b). Therefore, we constructed a knowledge graph that contains three types of entities (user, item, attribute) and their five kinds of relations, including "purchased_by (item→user)," "friend (user→user)," "like (user→attribute)," "belong_to (item→attribute)," and "also bought (item→item)."

Conversational path reasoning and experimental setup

We used Conversational Path Reasoning (CPR) (Lei et al., 2020b) algorithm for modeling the knowledge graph in the CRS framework. CPR chooses attributes to be asked and items to be recommended by following the paths in the knowledge graph. The preference score for a particular attribute is calculated as an average preference for the item that has the attribute. We simulated a conversational session to the user simulator adopted in Lei (2020a). Each turn in a conversation session, the system asked the user to list the top 3 values of the attribute or recommended the top k items. We compared three cases (applying only consumer needs attributes, applying only product design attributes, and applying both consumer needs attributes and product design attributes) to analyze the influence according to the taxonomy of attributes.

Findings and discussion

First, the taxonomy of fashion product attributes are classified into two dimensions: consumer needs and product design. We derived the value of each functional, expressive, aesthetic, shape, color, material, and detail attribute by comparing the relative information extracted from e-commerce. The taxonomy of attributes, values, and the extracted information is shown in Table 1. The CRS performance result showed that the taxonomy of consumer needs attributes could effectively improve the performance of fashion product recommendations in e-commerce. In general, applying consumer needs attributes outperforms other cases by achieving a higher success rate, and fewer average conversation turns. In a short conversation with the chatbot, it was confirmed to be better to ask about consumer needs attributes than product design attributes.

Table 1. Taxonomy of consumer needs and product design attributes

	Category	Attribute	Value	Extracted information
Consumer	Consumer needs	Functional	Fit	6 types of size
		Expressive	Value	5 types of price range
			Brand	112 clothing brands
		Aesthetic	Garment-body relationship	6 types of body shape
Product	Product design	Shape	Item	6 types of item
		Color	Hue	18 types of color
		Material	Fabric	23 types of fabric
		Detail	Detail	23 design details

Conclusions and further research

While many studies have investigated the importance of consumer needs theory and adapted it to clothing design development and evaluation, this is the first study in which the FEA consumer needs model has been applied to the chatbot service. This study makes significant theoretical contributions by expanding the FEA consumer needs model to be applied to digital product recommendation technology in an e-commerce environment.

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