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Application of the FEA consumer needs model in e-commerce: a conversational recommendation system for fashion products

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Abstract

With the rapid expansion of e-commerce, consumers increasingly rely on online platforms to purchase fashion products. However, the vast selection of products often leads to choice overload, making it challenging for consumers to find products that meet their needs. To address this challenge, we propose an advanced Conversational Recommender System (CRS) that applies a Functional, Expressive, and Aesthetic (FEA) consumer needs model. Using this model as a theoretical framework, this study constructs a taxonomy of consumer needs organized into categories and subcategories, each containing multiple attributes, and uses a Large Language Model (LLM) to apply it to review data, extracting attributes that influence purchase intention. Furthermore, CRS experiments were conducted to assess the impact of consumer needs attributes on recommendation performance. Our results indicate that the FEA model-based consumer needs taxonomy effectively categorizes consumer needs, with ease, good value for money, and leg contouring emerging as the most frequently mentioned attributes. Moreover, consumer needs attributes vary across different pants types, highlighting the importance of need-aware recommendations. Experimental evaluation of the CRS demonstrates that incorporating consumer needs attributes improves the recommendation success rates and reduces the average number of turns. Through the empirical application of the FEA model in the CRS, this study demonstrates its effectiveness in improving recommendation performance and its potential in enhancing consumer satisfaction.

Keywords: Conversational recommender system, FEA consumer needs model, Large language models, E-commerce, Fashion products

Introduction

Advances in digital technology have led to rapid expansion of e-commerce, with an increasing number of consumers engaging in online shopping (Lee et al., 2022). Online purchases of fashion products continue to grow, and consumers have to navigate through vast amounts of information to make the best choice among a wide range of products (Nagar & Gandotra, 2016). However, as the range of products increases, consumers face choice overload, which makes it difficult for them to make purchasing decisions (Mittal, 2016; Schwartz, 2004). To address this challenge, recommender systems

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have emerged, in particular, the Conversational Recommender System (CRS) has gained increasing attention as a way to provide personalized recommendations through real-time interaction in natural language (Chung et al., 2020).

Existing fashion recommender systems face a limitation in addressing consumer needs. For fashion products, consumers' purchase intentions are shaped by implicit needs encompassing functional, social, and visual considerations (Ling et al., 2022). However, existing research on fashion recommender systems focuses on the analysis of explicit product information, such as design, material, color, and brand, which often fail to address the implicit consumer needs (Elahi et al., 2023). This limitation underscores the need for a task-oriented CRS that integrates consumer needs (Sun & Zhang, 2018).

To address this limitation, this study proposes a novel approach that applies the Functional, Expressive, and Aesthetic (FEA) consumer needs model (hereafter referred to as the FEA model) to recommender systems, which serves as a framework for understanding purchase intention (Lamb & Kallal, 1992). The FEA model has been well established in the field as a conceptual framework that explains how consumers balance functional, expressive, and aesthetic needs when making decisions about fashion products. It is widely used in the fashion industry as an analytical tool to gain deeper insights into consumer needs. Its academic credibility is supported by extensive research demonstrating both its theoretical utility and practical effectiveness (Orzada & Kallal, 2021). In this study, we adopt this model as a theoretical foundation because it enables systematic analysis of consumer needs beyond explicit product information. In addition, reviews are an important source of data as they contain consumers' experiences and preferences, which, if systematically analyzed, can contribute to the design of need-aware recommender systems (Baek et al., 2012; Biswas et al., 2022).

Therefore, this study proposes a framework for fashion product recommendation that better captures consumer needs in online environments by applying the FEA model to recommender systems. Specifically, this study aims to (1) systematically analyze consumer needs and construct a FEA model-based consumer needs taxonomy and (2) integrate this taxonomy into a CRS to evaluate its recommendation performance compared with existing recommender systems. Recent studies have also demonstrated the potential of integrating deep learning-based content recommendation techniques into fashion systems to improve classification accuracy and product relevance (Suvarna & Balakrishna, 2024), underscoring the need for advanced technologies in this domain. In response, this study combines a Large Language Model (LLM) for review data analysis with a CRS implementation (Ghatora et al., 2024; Zablith, 2024), focusing on deriving consumer needs from unstructured data to provide tailored recommendations. By combining a theoretical framework with advanced technology, this study aims to extend the practical implementation of the FEA model in building need-aware recommender systems. To achieve these objectives, this study is guided by the following research questions:

RQ1. What are the key consumer need attributes related to pants in online environments?

RQ2. How do consumer needs attributes vary across different types of pants?

RQ3. How does the FEA model-based consumer needs taxonomy impact the recommendation performance?

Literature Review

Conversational recommender system

CRS is envisioned as the deep composition of conversational systems and recommender systems. CRS has recently emerged as an important area of research within the broader field of recommender systems (Siro et al., 2023; Sun & Zhang, 2018). Whereas traditional recommender systems generate recommendations by analyzing user behavioral data, CRS interacts with users in natural language and can proactively ask users about their preferences (Lei et al., 2020a).

The primary approaches in traditional recommender systems are content-based filtering and collaborative filtering. Content-based filtering recommends similar products based on a user's past preferences but is limited in its ability to provide diverse recommendations (Jagerman et al., 2019; Pardede et al., 2024; Wang et al., 2021). Collaborative filtering recommends products by analyzing the behavioral data of similar users but is limited in its ability to handle cold-start issues and data sparsity (Aijunid & Huchaiah, 2022; Guan et al., 2024). Furthermore, these methods rely on indirect information, such as a user's click or view history, which limits their ability to capture individual user preferences with precision (Aijunid & Huchaiah, 2022). CRS was developed to address these limitations by incorporating direct user feedback, enabling more accurate recommendations (Kim et al., 2025; Siro et al., 2023; Zhang, 2023).

Various methodologies have been explored for CRS, including knowledge-graph-based, reinforcement learning-based, and hybrid approaches. Among these, knowledge-graph-based CRS have received particular attention due to its ability to represent complex relationships between users and products (Lei et al., 2020a; Zhu et al., 2021). A knowledge graph is composed of relation triples (subject-relationship-object), which represent connections between entities and model interactions between users and products in a structured way. By incorporating product attributes, it effectively conveys product information to generate recommendations that align with user preferences. Furthermore, it enhances transparency by providing more interpretable explanations for recommendations (Ren et al., 2024; Xian et al., 2019).

Recent studies have explored various approaches that apply CRS to fashion recommendation. Vlachou and Macdonald (2024) proposed a CRS evaluation method that incorporates alternative items to reflect users' exploratory behaviors. Wu et al. (2022) analyzed the impact of user feedback on recommendation performance in a multimodal CRS and demonstrated that combining textual and visual information contributes to improving the accuracy of recommendations. However, relying on explicit product information remains insufficient to capture implicit needs within fashion recommender systems (Elahi et al., 2023; Shi & Yang, 2025; Zhang et al., 2022).

To overcome these limitations, a CRS needs to be extended by introducing additional attributes related to implicit needs. To achieve this, it is essential to develop a comprehensive taxonomy of attributes that systematically categorize consumer needs that influence purchase intentions. In the context of fashion products, consumers often evaluate products by considering nuanced aspects beyond product information attributes, such as symbolic meanings and emotional benefits. A well-defined taxonomy can integrate these subtle considerations into a CRS (Wand et al., 1995). Moreover, in knowledge-graph-based CRS, the recommendation performance can depend on how entities are

organized within the taxonomy. Therefore, constructing a taxonomy is crucial for modeling the complexity of consumer needs in fashion product recommendations.

FEA consumer needs model

Consumer needs models explain the motivation behind purchasing decisions, highlighting product development as critical research areas. Previous studies have highlighted key dimensions shaping consumer needs for fashion products, including identity expression, social influence, cultural meaning, and symbolic value (Brandt & Cory, 1989; Kaiser, 1997; Rosenblad-Wallin, 1985). Based on these studies, Lamb and Kallal (1992) introduced the FEA consumer needs model, which categorizes consumer needs into three categories: functional, expressive, and aesthetic. The FEA model is a framework that explains how consumers balance these three categories of needs and has been widely adopted for understanding purchase intention (Chae, 2020; Stokes & Black, 2012).

The FEA model divides consumer needs into three categories. Functional needs relate to the practical utility of clothing, encompassing aspects such as protection, ease, fit, mobility, and donning and doffing. These needs highlight the utilitarian function of clothing. Expressive needs involve the symbolic and communicative roles of clothing, as it conveys the wearer's identity, values, status, and social role. Aesthetic needs relate to the desire for beauty, which is influenced by cultural standards and assessed through artistic elements and design principles. Furthermore, it extends beyond clothing itself to include how it interacts with and complements the body.

The FEA model has been widely applied in product development, particularly for functional clothing such as sportswear and uniforms (Jin & Black, 2012; Orzada & Kallal, 2021). Recent studies have extended their applications to various fields, including smart clothing, sustainable design, and inclusive design. These findings highlight the model's adaptability and broad applicability (Koo, 2018; Nartker et al., 2024).

Previous studies employing the FEA model to analyze consumer needs have relied on qualitative and quantitative methods, such as surveys and interviews, focusing on specific consumer groups. However, there is a growing need to investigate consumer needs across large-scale online environments. To address this gap, it is essential to leverage extensive data from these online platforms and adopt advanced analytical methods that can capture the complexity and variety of consumer needs.

Consumer needs for pants

Consumer needs analysis serves as an essential component in product development. As the online environment expands, the growing diversity of product offerings underscores the importance of broadening the application of consumer needs analysis. Among various fashion items, pants demonstrate varied consumer needs influenced by season, occasion, and lifestyle. Pants, as a fundamental fashion item, are shaped by a complex interplay of functional, expressive, and aesthetic needs. Understanding how these needs vary is important for developing taxonomies that can be integrated into CRS as attributes. This complexity has motivated researchers to investigate consumer needs across different types of pants (Kim & Na, 2021).

Research has identified consumer needs for pants across different activities. Michaelson et al. (2018) analyzed consumers' priorities when selecting hiking pants and found

that fit, mobility, ease, protection, and donning and doffing were functional needs. Kim and Na (2021) examined reviews of cycling pants and reported that fit, padding quality, and material were highly valued. Furthermore, cost performance and design were also cited as relevant considerations.

Research has identified a range of consumer needs for jeans. Workman (1988) identified easy care and acceptable fit as functional needs, while utilitarian image, fashionable image, and brand symbolism linked to social status were categorized as expressive needs. Yun and Suh (2000) found that style, color, fit, body compatibility, and trends were considered aesthetic needs. They also highlighted personal expression, price, brand, social identification, and self-expression as expressive needs. Quality, mobility, and durability were considered functional needs. Kang (2023), through an analysis of reviews on online platforms, identified material thickness and seasonality as functional needs, whereas size, fit, coordination with shoes, and styling versatility were identified as aesthetic needs. Brand recognition and price performance were emphasized as expressive needs.

Research examining online consumer needs has provided broader insights. González et al. (2021) identified product quality, psychological comfort, and social perception as central consumer needs in online environment. Hong and Jin (2011) analyzed reviews on online platforms and found that consumers assess products based on functional, aesthetic, economic, emotional, social, practical needs and value for money.

This literature review demonstrates that consumer needs for pants vary across different types of pants, encompassing functional, expressive, and aesthetic needs. Research examining online consumer needs suggests that these needs extend beyond specific product types to broader shopping contexts. The extensive data available through consumer reviews on online platforms presents opportunities to develop taxonomies to improve the performance of CRS. These findings support the application of FEA model in implementing need-aware recommender systems for online environments.

Methods

This study aims to analyze consumer needs for pants in online environments, construct an FEA model-based consumer needs taxonomy, and evaluate its effectiveness in CRS. To achieve this, this study collected product and review data from online platforms and constructed taxonomies of product information and consumer needs. The collected data were analyzed to extract attributes from the taxonomies, which were then integrated into a CRS to evaluate its recommendation performance (Fig. 1).

Data collection and preprocessing

Data on pants in the women's fashion category were collected through web crawling on Musinsa (www.musinsa.com). Musinsa, the largest online fashion platform in South Korea, was selected as the data source due to its diverse range of products and extensive reviews. Data collection was conducted between May and June 2024, resulting in 4000 product entries and 275,998 reviews, written predominantly in Korean.

Preprocessing was performed separately for product and review datasets. For product data, duplicate entries were removed, and missing values were imputed. When key attributes such as material or color were missing, relevant information was extracted from product descriptions. For review data, text cleaning and sentiment analysis were

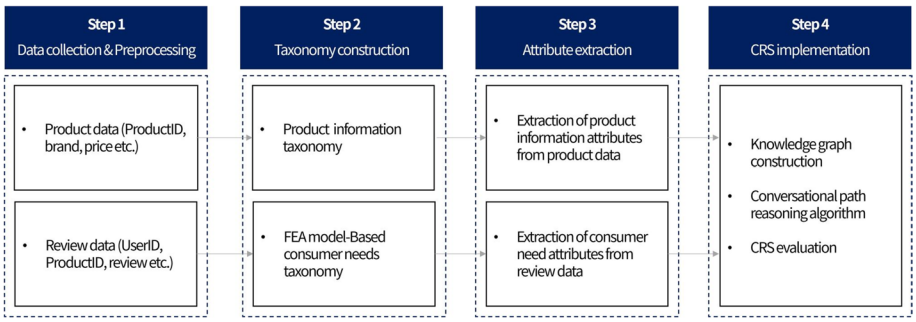


Fig. 1 Research process

performed. The text cleaning was conducted in Python 3.9 using regular expressions for removal of noise including emoticons, special characters, repeated characters, and incorrect spellings, and pandas 2.2 for data handling. Subsequently, sentiment analysis was implemented using TensorFlow 2.11 with a Gated Recurrent Unit (GRU) model. The GRU model was configured with embedding layers and trained using the Adam optimizer with binary cross-entropy loss function. Text vectorization was conducted using TensorFlow to convert reviews into numerical sequences. The trained model achieved a validation accuracy of 0.92 and was used to classify review sentiments, filtering for positive reviews with sentiment scores above 0.5 to ensure that extracted consumer needs reflect satisfied purchasing experiences rather than complaints or dissatisfaction (Kaur & Sharma, 2023). This process resulted in 80,116 positive reviews retained for analysis.

Taxonomy construction

The taxonomies are constructed along two dimensions: (1) product information and (2) consumer needs. The product information taxonomy consists of categories including brand, price, color, fit, material, and details, each with their corresponding attributes. This taxonomy was developed by referencing product attribute categories used by existing online fashion platforms to ensure practical applicability in online environments (Cho & Kim, 2004). In contrast, the taxonomy for consumer needs combines a conceptual approach based on the existing literature and the FEA model as a theoretical foundation with empirical analysis derived from review data (Bailey, 1984). The specific categorization process is outlined as follows.

First, previous studies were reviewed to identify consumer needs associated with pants, which were then organized according to the categories of the FEA model. Because consumer considerations may vary across different types of pants, various pants types such as hiking, casual, and formal pants were included in the analysis. Second, review data analysis was conducted to examine how well the consumer needs identified in prior research are reflected in reviews. While prior research has introduced broad theoretical concepts to explain consumer needs, these are often too general for practical application. To refine them, keywords extracted from the review data were compared with the existing concepts, resulting in a more concrete set of attributes. For example, González et al. (2021) suggest that consumers consider social value when purchasing products in online environments. However, this concept can be interpreted broadly depending on

the research context. In this study, social value was specified in terms of how consumers express their social identity by categorizing attributes, such as teen fashion, young adult fashion, mature fashion, student, and working professional attire. Through this process, a total of 30 attributes were identified to construct a taxonomy of consumer needs organized into categories and subcategories, with each category containing multiple attributes. The complete taxonomy is presented in Table 1.

Attribute extraction

Based on the taxonomies established in the previous section, the attributes were extracted to represent two dimensions: product information and consumer needs.

Product information attributes were extracted from product data. These attributes were organized based on product attribute categories used by existing online fashion platforms. The type category includes seven attributes derived from the actual product attributes used by the data collection platforms. Color attributes required standardization due to varied user descriptions and brand-specific terminology, resulting in 15 representative color attributes. Material, fit, and details attributes were organized based on commonly used attributes across online fashion platforms for pants, grouping material into seven attributes, fit into six attributes, and details into five attributes. Brand attributes included 419 distinct brands identified from the data. Price attributes were divided into five tiers based on price distribution patterns (Table 2).

Consumer needs attributes were extracted through an analysis of review data. To analyze the review data, an LLM-based attribute extraction method was applied. Previous studies have used rule-based methods or machine learning methods, but these methods struggle to effectively handle irregular language used in large-scale review data (Barroca et al., 2022; Ou et al., 2018). To address this challenge, GPT-4o-mini, developed by OpenAI, was adopted for attribute extraction, as it has gained significant attention recently in natural language processing (Rasheed et al., 2024). GPT-4o-mini was chosen due to its lightweight nature, computational efficiency, and reliable performance in natural language processing. Additionally, using zero-shot learning allowed attribute extraction without requiring labeled training data.

For attribute extraction, a customized prompt was designed to reflect the consumer needs attributes of the taxonomy. The prompt defines the (1) role, (2) task, (3) attribute definitions, and (4) output format in JavaScript Object Notation (JSON). To measure response reliability, a relevance score was introduced. Following established practices in attribute extraction using LLM, the model was instructed to internally evaluate its confidence in the semantic match between each review and extracted attribute (Yang et al., 2024). The relevance score ranged from 0 to 1, serving as an indicator of reliability levels, with higher values indicating higher reliability. These scores were included in the JSON output to enable filtering of unreliable attributes and facilitate validation. Table 3 illustrates the prompt structure, while Table 4 demonstrates the transformation of reviews into structured JSON outputs containing attributes and their corresponding relevance scores. The complete prompt template is provided in Appendix A.

To validate the reliability of the extracted attributes, a sample of 1000 reviews was manually annotated by two fashion experts. Of these, 400 reviews were used to

Table 1 FEA model-based consumer needs taxonomy

Category	Subcategory	Attribute	Definition	Research
Functional	Protection	Warmth	Retains body heat and minimizes external heat loss	Michaelson et al. (2018) Kang (2023)
		Durability	Structured fabrics that maintain their integrity	Michaelson et al. (2018) Kim and Na (2021) Yun and Suh (2000)
	Mobility	Lightweight	Fabric that has a relatively low weight	Michaelson et al. (2018) Yun and Suh (2000)
		Elasticity	Stretchable fabric providing flexibility and resilience	
	Comfort	Waterproof	Prevents water penetration with waterproof fabric	Michaelson et al. (2018)
		Windproof	Prevents wind penetration with protective fabric	
	Donning	Ease	Provides physical ease and relaxation	Michaelson et al. (2018) Workman (1988)
		Easy maintenance	Easy to clean, dry, and maintain with minimal effort	Michaelson et al. (2018) Workman (1988)

Table 1 (continued)

Category	Subcategory	Attribute	Definition	Research
Expressive	Role	Teen fashion	Clothing reflecting trends and preferences of teenagers	Workman (1988) González et al. (2021) Yun and Suh (2000)
		Young adult fashion	Clothing reflecting trends and preferences of young adults in their twenties	
		Mature fashion	Clothing reflecting trends and preferences of individuals in their thirties	
		Working professional	Clothing typically worn by office workers	
		Student	Clothing typically worn by students	
	TPO	Business wear	Clothing suitable for professional business settings	González et al. (2021) Yun and Suh (2000)
		Wedding guest wear	Clothing suitable for formal events such as weddings	
		Sportswear	Clothing suitable for exercise or physical activities	
		Loungewear	Clothing suitable for relaxation at home	
		Travel wear	Clothing suitable for travel	
	Status	Good value for money	Represents a balance of quality at an affordable price	Kim and Na (2021) Workman (1988) González et al. (2021) Yun and Suh (2000) Kang (2023)
		Luxury	Represents refined quality with premium materials	Workman (1988) González et al. (2021) Yun and Suh (2000)
	Self-esteem	Positive feedback	Receiving compliments or inquiries about clothing from acquaintances	González et al. (2021) Yun and Suh (2000)

Table 1 (continued)

Category	Subcategory	Attribute	Definition	Research
Aesthetic	Body/garment relationship	Opaque	Prevents see-through by using opaque fabrics for full coverage	Yun and Suh (2000) Kang (2023)
		Groin coverage	Design that minimizes emphasis on the groin area	
		Waist contouring	Design that emphasizes or provides shaping effects on the waist	
		Hip contouring	Design that highlights the hip or pelvic line	
		Leg contouring	Design that makes legs look long and slim	
	Matching item	Sneakers	Design that pairs well with sneakers	Kang (2023)
		Sandals	Design that pairs well with sandals	
		Formal shoes	Design that pairs well with dress shoes	
	Design principle	Trends	Emphasizes up-to-date fashion elements aligned with current trends	Yun and Suh (2000) Workman (1988)

Table 2 Extracted product information attributes

Category	Attribute	Count
Type	Jeans, Leggings, Slacks, Overalls, Cargo pants, Chinos, Jogger	7
Brand	1989STANDARD, 1993STUDIO, 27Y, 38COMEONCOMMON…	419
Price	0 ~ 43,900, 43,900 ~ 54,360, 54,360 ~ 69,000, 69,000 ~ 89,000, 89,000 ~	5
Color	White, Gray, Charcoal, Black, Pink, Light blue, Blue, Navy, Beige, Brown, Green, Khaki, Red, Yellow, Purple	15
Fit	Baggy, Bootcut, Skinny, Straight, Slim, Wide	6
Fabric	Nylon, Rayon, Linen, Cotton, Wool, Polyurethane, Polyester	7
Detail	Roll-up, Banding, Washing, Pleats, Distressed	5

Table 3 Structure of the prompt

Component	Description
Role	You are a fashion specialist
Task	You will be presented with user reviews about pants. Your task is to extract relevant fashion attributes and assign a relevance score…
Attribute definitions	Warmth: Retains body heat and minimizes external heat loss…
Response format	Return results in JSON format {"attribute": score, "attribute": score, …}

Table 4 Input and output example for consumer needs attributes extraction

Component	Example
Input	It's comfortable and has a classic wide fit. I bought it in multiple colors for my everyday work outfits
Output	{"Ease": 0.8, "Working Professional": 0.9}

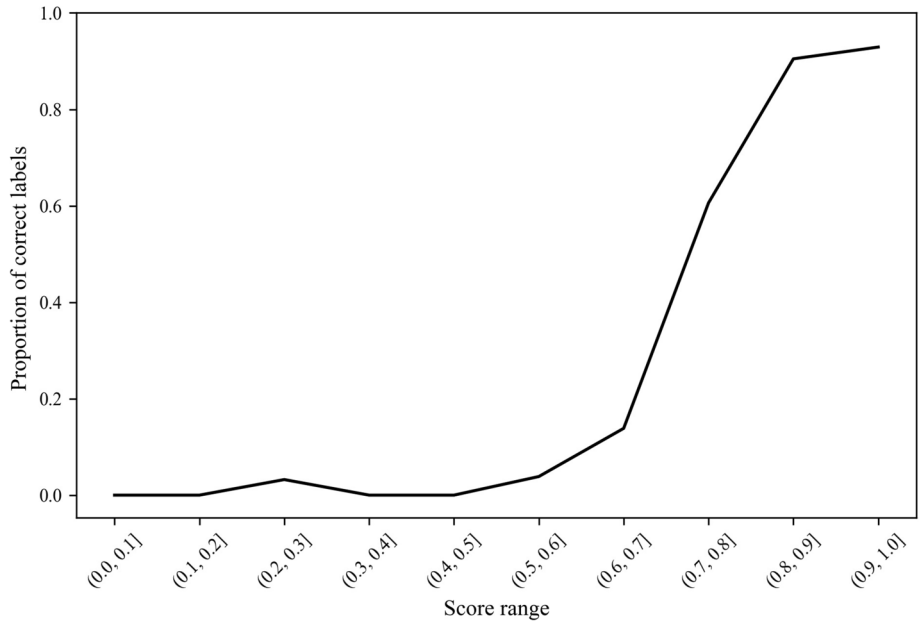


Fig. 2 Proportion of correct labels across relevance score range

optimize the relevance score threshold for filtering reliable outputs, while the remaining 600 reviews were used to evaluate model performance using precision, recall, and F1-score.

To determine whether the relevance scores effectively indicated reliability levels, the alignment between these scores and human annotations was examined. The relevance scores were divided into ten intervals, and the proportion of correctly predicted labels within each interval was calculated. The analysis showed that agreement with human annotations was low at lower scores but increased sharply for scores above 0.7. This positive relationship supports the use of relevance scores as indicators for filtering out unreliable attributes (Fig. 2).

Based on this validation, optimal thresholds for relevance scores were established. For attributes that appeared at least 30 times in the annotated data, individual thresholds were optimized to maximize the F1-score. For attributes that appeared fewer than 30 times, individual threshold optimization was not feasible due to insufficient data, so the validated threshold of 0.7 was uniformly applied.

The validation results demonstrated the reliability of the LLM-based attribute extraction method. Using the optimized thresholds, the model achieved an F1-score of 0.88, a precision of 0.86, and a recall of 0.90, indicating strong alignment between

the extracted attributes and human annotations. Based on these results, attributes above the established thresholds were retained for subsequent analysis. The validated attributes were then examined in two ways: analyzing their frequency across the entire review data and comparing their distribution across seven different types of pants to understand variations in consumer needs.

CRS implementation

Knowledge graph construction

In this study, a knowledge graph was constructed to implement a CRS that incorporates FEA model-based consumer needs taxonomy. The graph connects products with consumer needs attributes identified from review data analysis. Products with at least three reviews were selected to ensure meaningful product-attribute connections. The data was then divided into training and test sets to evaluate the recommendation performance.

For performance comparison, five knowledge graph configurations were constructed based on different combinations of attributes from the product information and consumer needs taxonomies: a baseline model using only product information attributes (PI), and extended models that include functional attributes (PI + F), functional and expressive attributes (PI + FE), functional and aesthetic attributes (PI + FA), and functional, expressive, and aesthetic attributes (PI + FEA). The statistics for each configuration are summarized in Table 5.

The knowledge graph defines users, products, and attributes as its main entities. Attributes are organized into categories, with each category containing multiple specific attributes. The knowledge graph incorporates seven key relations: "purchased" (product → user), "friend" (user → user), "like" (user → attribute), "belong to" (product → attribute), "belong to category" (product → category), "viewed together" (product → product), and "connected" (category → attribute). This graph structure enables the system to leverage both explicit product information and implicit consumer needs.

Experimental setup and performance evaluation

In this study, a Conversational Path Reasoning (CPR) was integrated into the CRS to enable conversational recommendations based on knowledge graphs. CPR is an

Table 5 Statistics of datasets

Dataset		PI	PI + F	PI + FE	PI + FA	PI + FEA
Entities	User	3448	3448	3448	3448	3448
	Product	2311	2311	2311	2311	2311
	Category	8	9	10	10	11
	Attribute	365	373	386	382	395
Relations	Purchased	17,100	17,100	17,100	17,100	17,100
	Friend	344,748	344,738	344,748	344,738	344,738
	Like	71,810	81,088	91,876	92,240	103,028
	Belong to	28,844	33,064	36,536	36,164	39,636
	Belong to category	33,472	37,692	41,164	40,792	44,264
	Viewed together	10,942	10,942	10,942	10,942	10,942
	Connected	732	748	774	766	792

algorithm that identifies recommendation paths through user interactions. It maps the dialogue to a path within the knowledge graph, helping the system recommend products that contain the attributes users have preferred (Lei et al., 2020b). To evaluate CRS performance, a user simulator proposed by Lei et al. (2020a) was used to simulate conversational recommendation sessions. Each session involves multiple dialogue turns with iterative preference elicitation and recommendation. At each dialogue turn, the system either presents three attributes to gather user preferences or recommends three products that match the collected preferences. The experiments were implemented using Python 3.9 with PyTorch 2.6 and CUDA 11.8

Two experiments were conducted to assess the impact of consumer needs attributes on recommendation performance. In the first experiment, a baseline model using only product information attributes (PI) was compared with a model that incorporated functional, expressive, and aesthetic attributes (PI + FEA). The second experiment adopted a stepwise approach to examine the individual contribution of each consumer needs attributes. This stepwise experiment first tested a model with functional attributes (PI + F), followed by models that added expressive (PI + FE) or aesthetic attributes (PI + FA) to the functional attributes. Finally, a model incorporating functional, expressive, and aesthetic attributes (PI + FEA) was tested. The stepwise approach reflects the understanding that functional, expressive, and aesthetic needs are interrelated (Lamb & Kallal, 1992), with research suggesting that functional needs should be addressed before incorporating expressive and aesthetic needs (Orzada & Kallal, 2021).

For performance evaluation, the success rate at turn t (SR@t), average turns (AT), and failure rate (FR) were used as performance metrics. SR@t measures the cumulative success rate of recommendations up to a specific dialogue turn t (Sun & Zhang, 2018). A higher SR@t value indicates a higher recommendation success rate at that turn. AT measures the average number of turns required per session, indicating how quickly the system provides recommendations, with lower values indicating better performance. FR measures the recommendation failure rate, with lower values indicating better performance.

Results

Consumer needs for pants in online environments

The review data analysis identified the most frequently mentioned consumer needs attributes, as shown in Table 6. Among the functional attributes, ease was the most frequently mentioned attribute, consistent with previous research on consumer needs for pants (Michaelson et al., 2018; Workman, 1988). This finding suggests that ease continues to be a primary consideration in pants. Other prominent functional attributes included lightweight, warmth, durability, easy maintenance, and waterproof and windproof attributes.

Among the expressive needs, good value for money was the most frequently mentioned attribute. This finding aligns with previous studies demonstrating that consumers prioritize cost performance (González et al., 2021; Kim & Na, 2021; Workman, 1988). Positive feedback and luxury were frequently mentioned, suggesting that expressive needs related to social image are important for consumers. Role-related attributes also mentioned, with teen and young adult fashion both showing relatively high frequencies,

Table 6 Extracted consumer needs attributes from review data

Rank	Attribute	*f*	Category	Rank	Attribute	*f*	Category
1	Ease	25,954	Functional	16	Sneakers	1117	Aesthetic
2	Lightweight	8022	Functional	17	Travel wear	807	Expressive
3	Warmth	7705	Functional	18	Working professional	783	Expressive
4	Good value for money	5872	Expressive	19	Loungewear	569	Expressive
5	Durability	5871	Functional	20	Opaque	567	Aesthetic
6	Leg contouring	3989	Aesthetic	21	Teen fashion	395	Expressive
7	Trends	3921	Aesthetic	22	Young adult fashion	322	Expressive
8	Waist contouring	3329	Aesthetic	23	Waterproof	186	Functional
9	Elasticity	3136	Functional	24	Formal shoes	175	Aesthetic
10	Positive feedback	2967	Expressive	25	Business wear	172	Expressive
11	Student	1643	Expressive	26	Windproof	169	Functional
12	Sportswear	1386	Expressive	27	Groin coverage	155	Aesthetic
13	Easy maintenance	1346	Functional	28	Sandals	44	Aesthetic
14	Luxury	1189	Expressive	29	Mature fashion	32	Expressive
15	Hip contouring	1153	Aesthetic	30	Wedding guest wear	28	Expressive

whereas mature fashion was mentioned far less often. TPO-related attributes such as sportswear and travel wear were also mentioned.

Regarding aesthetic needs, leg, waist, and hip contouring were the most frequently mentioned, reflecting the importance of body contouring to consumers. This finding consistent with previous research that positioned it among essential aesthetic needs (Kang, 2023; Yun & Suh, 2000). Trends were another frequently mentioned attribute among consumers. When discussing matching items, sneakers appeared most often, while formal shoes and sandals were mentioned much less often. Other notable attributes included opaque and groin coverage. These attributes, rarely addressed in previous research, indicate that consumers prioritize design elements that provide appropriate coverage, particularly with thin materials or fitted styles.

Comparison of consumer needs across pant types

A comparison of consumer needs attributes across seven pant types revealed that ease was consistently mentioned across all pant types, whereas other attributes varied by pant type (Fig. 3).

For joggers, consumers emphasized functional needs, particularly ease, warmth, lightweight, durability, and elasticity. Among expressive and aesthetic attributes, good value for money and trends were frequently mentioned. For leggings, the most frequently mentioned attributes were ease and elasticity, both of which were functional attributes. Expressive attributes related to TPO, such as sportswear, and aesthetic attributes related to body/garment relationships, such as leg contouring and groin coverage, were also frequently mentioned. For slacks, functional attributes such as ease and durability were most frequently mentioned. Expressive attributes related to roles were mentioned, particularly working professionals, and aesthetic attributes such as leg and waist contouring, were also mentioned. For cargo pants, functional needs focused on ease and lightweight attributes. TPO-related expressive attributes, particularly travel wear, were also mentioned. Trends were frequently mentioned among aesthetic attributes. For

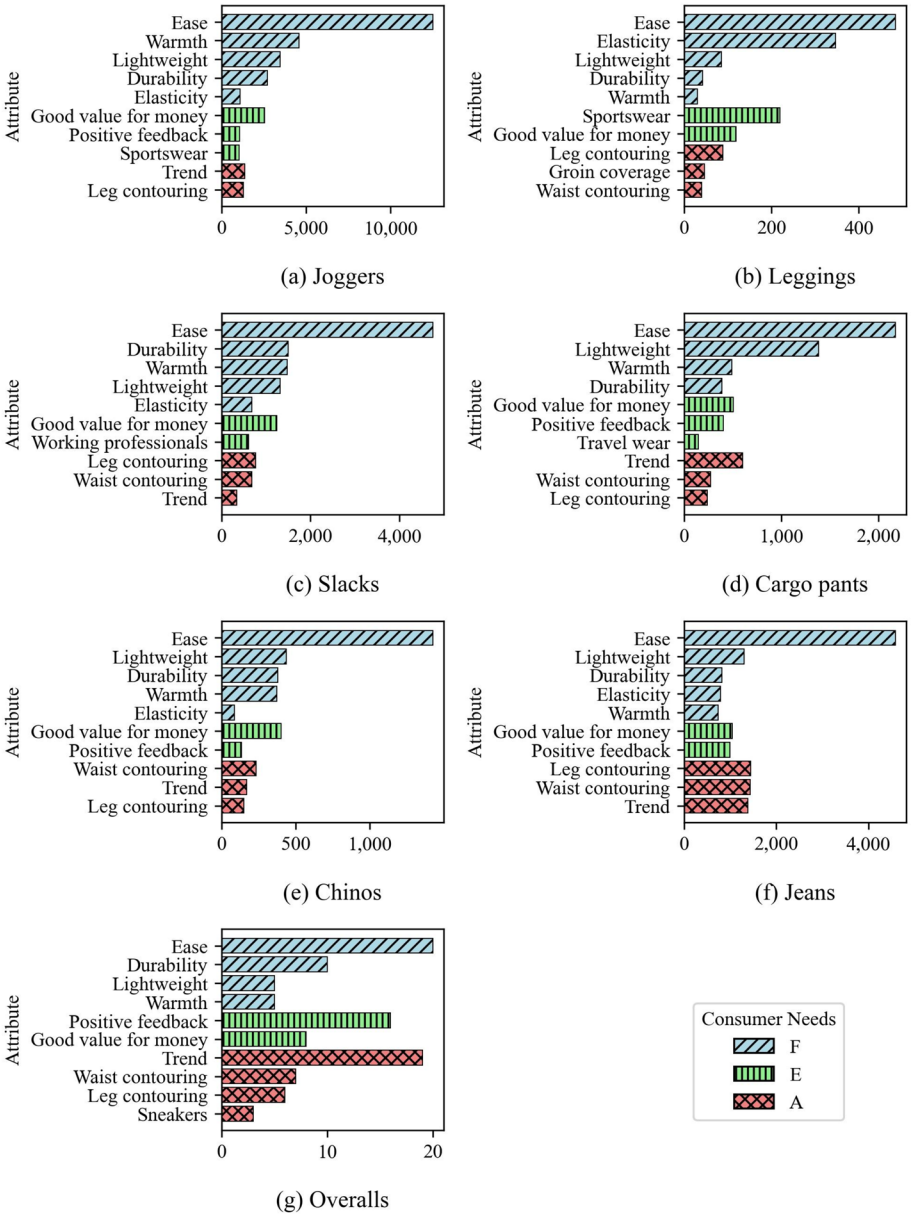


Fig. 3 Comparison of the top 10 consumer needs attributes across pant types

chinos, ease was the most frequently mentioned functional attribute, with good value for money also frequently mentioned as an expressive attribute. Additionally, waist contouring and trends were frequently mentioned as aesthetic attributes. For jeans, consumers primarily emphasized functional needs, though aesthetic needs were more emphasized than expressive needs. Among these aesthetic needs, leg and waist contouring, along with trends, were frequently mentioned. For overalls, functional, expressive, and aesthetic attributes were mentioned with similar frequency, suggesting balanced consumer needs for this pant type.

These findings confirm that consumer needs vary by pant type due to different priorities for functional, expressive, and aesthetic attributes. This highlights the necessity

of a need-aware recommendation that integrate both product information attributes and consumer need attributes.

Application of the FEA model in CRS performance

To evaluate the overall impact of consumer needs attributes on recommendation performance, an experiment was conducted to compare the PI model, which utilizes only product information attributes, with the PI + FEA model, which incorporates consumer needs attributes. The results indicate that integrating consumer needs attributes improves overall recommendation performance.

In the PI model, SR@5, SR@10, and SR@15 were 0.06, 0.65, and 0.86, with AT was 8.82 and FR was 13.91%. In contrast, in the PI + FEA model, SR@5 increased to 0.32, SR@10 increased to 0.81, and SR@15 increased to 0.91, while AT and FR decreased to 7.25 and 9.09%, respectively. These findings suggest that incorporating consumer needs attributes enhances success rates, while reducing the average number of turns. A comparison of the CRS performance metrics, including SR@5, SR@10, SR@15, AT, and FR, is summarized in Table 7.

To investigate the individual contribution of consumer needs attributes, an experiment was conducted in which functional, expressive, and aesthetic attributes were added incrementally. The results indicate that different attribute categories influenced recommendation performance in various ways.

The inclusion of functional attributes enhanced initial success rates but had limited impact on final success rates. In the PI + F model, SR@5 increased to 0.28, indicating improved initial success rates, while SR@10 and SR@15 improved to 0.78 and 0.87, respectively. Additionally, the FR decreased to 12.93%, and AT decreased to 6.93. However, the limited improvement in SR@15 suggests that functional attributes alone cannot maximize the final success rates.

Building upon these findings, the addition of expressive attributes played a crucial role in enhancing recommendation performance. In the PI + FE model, SR@15 increased to 0.89, and AT reached its lowest value of 6.69. This demonstrates that expressive attributes contributed to more targeted recommendations. Notably, SR@10 increased to 0.82, indicating substantially improved success rates even within fewer turns.

In contrast, the addition of aesthetic attributes showed a different pattern, improving success rates while requiring more turns. In the PI + FA model, SR@15 was at 0.89 but AT increased to 7.08. This suggests that although aesthetic attributes improve success rates, they also require additional attribute exploration, leading to a longer average number of turns.

Table 7 Performance metrics of CRS models

Experiment	SR@5	SR@10	SR@15	Average turns	Failure rate (%)
PI	0.06	0.65	0.86	8.82	13.91
PI + F	0.28	0.78	0.87	6.93	12.93
PI + FE	0.30	0.82	0.89	6.69	11.11
PI + FA	0.23	0.80	0.89	7.08	10.90
PI + FEA	0.21	0.80	0.91	7.25	9.09

In the PI+FEA model, which incorporated all attributes, SR@15 reached its highest value of 0.91, and FR reached its lowest value of 9.09%, demonstrating the highest success rates. However, AT increased to 7.25, indicating that incorporating all attributes increases the average number of turns despite improving success rates.

In summary, incorporating consumer needs attributes improves overall recommendation performance. The addition of functional attributes enhanced the initial success rates. Expressive attributes played a key role in accelerating the recommendation process by increasing the success rate within a fewer average number of turns. Furthermore, incorporating aesthetic attributes is necessary to achieve the highest final success rates. However, because incorporating all attributes increased the number of turns, it is important to balance attribute combinations to achieve optimal performance.

Discussion

Our results indicate that the FEA model-based consumer needs taxonomy plays a crucial role in CRS. The choice of taxonomies applied as entities within the knowledge graph affects recommendation performance. In particular, leveraging consumer needs attributes enables the CRS to effectively capture consumer preferences through conversational interactions, enhancing success rates while reducing the average number of turns. To illustrate the practical benefits of integrating consumer needs attributes into CRS, Fig. 4 illustrates the CRS process, comparing two recommendation approaches: one relying on product information attributes and the other incorporating consumer needs attributes.

Figure 4a represents the CRS approach that relies on product information attributes. For example, when a consumer searches for pants, the system recommends products based on product information such as type, color, and material. However, this method is limited by its reliance on simple attribute filtering, which fails to capture implicit needs. In contrast, Fig. 4b shows the integrated approach that combines product information and consumer needs attributes. This approach enables need-aware recommendations tailored to consumer preferences.

In this integrated approach, the knowledge graph serves as the foundation for identifying relevant products. The CRS uses this knowledge graph to guide users through conversations toward relevant product recommendations. The recommendation process follows a path within the graph, where the system initiates a recommendation from the user node and explores different attributes to identify the most suitable product. At each turn, the system asks users to select from three attributes, determines the next step based on their responses, and provides recommendations that match their preferred attributes.

Based on this graph structure, the CRS dynamically adjusts its recommendation path through interactions, continuously improving its suggestions to match their preferred attributes. When a consumer reject presented attributes or expresses dissatisfaction with a recommended product, the system explores alternative attributes within the same category or establishes a new recommendation path. This iterative process ensures recommendations better align with consumer needs. The integration of knowledge graphs and consumer needs attributes offers significant opportunities for practical implementation, especially in e-commerce.

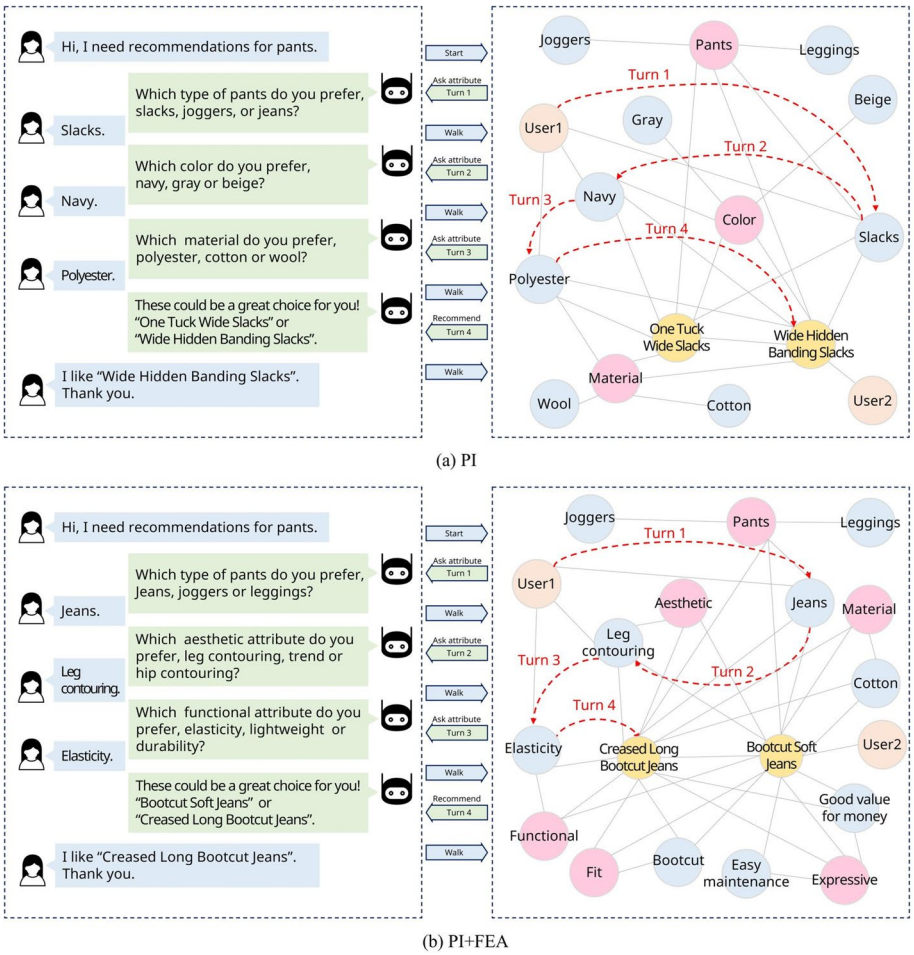


Fig. 4 Comparison of the CRS process: (a) using product information attributes only and (b) integrating product information and consumer needs attributes. In this illustration light orange, light pink, light blue, and light gold node represent the user, main attribute, attribute and items respectively

Conclusions

This study applies the FEA model to fashion product recommender systems by designing a CRS that addresses consumer needs and evaluates its performance. Traditional fashion recommender systems rely on explicit product information, limiting their ability to capture implicit needs. To overcome this limitation, this study constructs a taxonomy of consumer needs based on the FEA model and integrates it into the CRS, thereby proposing an approach to enhance recommendation performance.

The findings demonstrate that the FEA model-based consumer needs taxonomy effectively categorizes consumer needs, with its validity supported by review data analysis. Experimental results further show that integrating consumer needs attributes into the CRS improves recommendation performance. Specifically, functional attributes support early-stage recommendation success, expressive attributes contribute to rapid recommendations with fewer turns, and aesthetic attributes enhance final success rates, but tend to increase the number of turns needed to reach a recommendation.

This study makes theoretical and practical contributions by expanding the academic foundation of the FEA model and supporting the digital transformation of the fashion industry. From an academic perspective, this study makes three key contributions. First, it applies the FEA model to online environments by incorporating review data, thus constructing a consumer needs taxonomy and validating its effectiveness. Unlike previous studies that introduced theoretical concepts without empirical validation, this study examines these concepts using review data and refines them into more specific attributes to develop a system that captures consumer needs. Second, this study empirically tests the integration of the FEA model into the CRS, demonstrating that incorporating consumer needs attributes enhances recommendation performance compared to traditional models that rely on product information attributes. This contributes to the advancement of fashion theory by integrating it with technology. Third, by applying LLM to review data analysis, this study expands the methodological scope of text mining in the fashion industry. The empirical results confirm that LLM-based method can effectively extract consumer needs from review data, supporting recommender systems.

In addition, the findings of this study offer practical contributions to the development of AI-powered, data-driven, personalized recommendations for e-commerce. First, by proposing a conversational interface for recommendations, this study enables more refined personalization in online environments. Second, the CRS based on the FEA model is designed to recommend products, which can enhance consumer satisfaction and facilitate product discovery on online platforms.

Although this study makes meaningful contributions to the advancement of recommender systems for fashion products, several limitations should be acknowledged. First, this study focuses exclusively on pants, which may restrict its applicability to other items, such as tops, outerwear, and accessories, where consumer needs may vary. Future research should expand the scope of the analysis to include a broader range of items to enhance the generalizability of the findings. Second, while the LLM-based attribute extraction method demonstrated strong overall performance, it remains susceptible to generating inaccurate outputs. In particular, the model occasionally produced unreliable attributes, especially in reviews containing ambiguous or figurative expressions. To address this limitation, a validation process was implemented combining human annotation and filtering based on relevance scores. Relevance scores helped filter unreliable attributes, such as hallucinated or contextually inappropriate attributes, using optimized thresholds. While this approach improved overall accuracy, it revealed additional challenges with rare or nuanced attributes, especially those that appeared fewer than 30 times, which remained difficult to extract reliably due to limited context. To further enhance the reliability of LLM-based attribute extraction, future research should incorporate additional data and explore more sophisticated validation processes.

Addressing these limitations will facilitate the design of more effective recommender systems that can capture implicit consumer needs. Further research should explore the applicability of the FEA model across diverse consumer groups and items to improve its generalizability. Additionally, studies should prioritize the collection of additional data to strengthen the robustness of the model. In addition, incorporating

negative review data may help better capture the full spectrum of consumer needs. These advancements will enable recommender systems that apply the FEA model to provide more satisfying experiences for consumers in the fashion industry.

Abbreviations

CPR Conversational Path Reasoning
CRS Conversational Recommendation System
FEA Functional, Expressive, and Aesthetic

Supplementary Information

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Supplementary material 1.

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Author contributions
HA and YC, as corresponding authors, jointly conceptualized the research and contributed to the interpretation and refinement of the manuscript. HP conducted the research and drafted the initial manuscript. HP and SK developed the LLM model and conducted the data analysis. YC additionally designed and reviewed the LLM modeling experiments. All authors reviewed and approved the final manuscript.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical approval and consent to participate
Not applicable.

Competing interests
The authors declare that they have no competing interests. Hyosun An is an Editorial Board Member of Fashion and Textiles. Editorial Board Member status has no bearing on editorial consideration.

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