

Fashion Recommendation System and its Impact on Consumers' Purchase Decision Making

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Abstract:

Consumers' fashion preferences are influenced by a range of variables including: demographics, location, personal preferences, social influences, age, gender, season, and culture. Additionally, recent study on fashion recommendation demonstrates that fashion preferences differ not only from one country to another but also from one city to another. Combining fashion preferences with the aforementioned variables related to clothing selections that may help researchers better understand customer preferences by transmitting the picture attributes. As a result, fashion designers and merchants benefit by studying client preferences and suggestions. Additionally, consumers' data gathered from clothing choices and product preference have become available on the Internet in the form of text, opinions, images and pictures. Both online and offline fashion retailers are using these platforms to reach billions of users who are active on the Internet. Therefore, e-commerce has become the predominant channel for shopping in the recent years.. With the development of e-commerce technology, A large number of consumers prefer to buy garments through e-commerce websites. But on the internet, where the large majority of choices have become overwhelming, it is necessary to filter, prioritize, and present pertinent information quickly according to every one's preferences. Recommendation systems (RSs) solve this problem through sifting a significant amount of dynamically created data to offer customers personalized content and suggestions. The suggestions relate to various decision-making processes, such as what items to buy, what music to listen to, or what online news to read. This paper examines the various traits and potentials of the prediction techniques used in Fashion Recommendation systems (FRs).

Keywords:

Recommendation systems (RSs); Fashion recommendation system (FRs); Collaborative filtering (CF); Content-based filtering (CB); Hybrid filtering technique.

Paper received 11th August 2022, Accepted 14th November 2022, Published 1st of January 2023

1- Introduction:

Humans rely on recommendations from others in their daily lives, whether through word-of-mouth (WOM), hotel guides, restaurants, movies, book reviews, letters of recommendation, and other channels. The consumer's online shopping experience has been transformed by modern technology, particularly artificial intelligence, and so-called recommendation systems (RSs) have just recently emerged. These systems are used in many different contexts, including: music, newspapers, books, articles, and commercial websites like Amazon, social networking sites, and movie watching and rating sites. RSs are information filtering methods that address the issue of information overload. This happens by selecting the most important information fragments from a vast volume of dynamically created data, this data is based on the user's preferences, interests, or observed behavior about the item. Based on the user's profile, a recommender system can determine if they will prefer an item or not. The prototypical use case for a RS occurs regularly

in e-commerce environments. (Robin Burke et al.: 2011) Both service providers and users benefit from RSs. Initially, they lower the transaction costs associated with locating and choosing products in an online buying setting, due to the fact that their efficient product sales is in an increasing slope, thus boosting revenues.

Based on the consumer's browsing and previous purchase history, fashion recommendation systems (FRs) typically offer targeted recommendations. The user's social circle, fashion product qualities, image parsing, fashion trends, and consistency in fashion styles are all essential aspects for social network-based FRs. As a result, it was seen that the system has an impact on the user's purchase decisions.

Statement of the problem:

The research problem lies in trying to answer the following question:

- Is it possible for fashion marketing to fully utilize the technology behind fashion recommendation systems FRs as more and more firms start to refine their marketing strategies?

- Defining the general idea of the FRs technique and estimating the extent of its influence on the fashion industry.

Objectives:

The study revealed a new technology (recommendation systems) in fashion industry and measures its impact on the consumers' buying decisions to further enhance its efficiency.

- This research aims to deepen the understanding of decision-making behaviors under the influence of RS use and consumer attitudes toward the RS use.
- This review study aims to fill the research gap by thoroughly examining the approaches taken, and the overall performance of the modern FRs.
- This research provides a guideline for future research in the domain of RS.

Importance:

The purpose of this study is to understand the research trends in the field of recommendation systems.

The study aims to give readers insight on AI applications that claim to improve the FRs system and trigger higher purchases and evaluate the relationship between the use of RSs and the decision-making processes.

Hypothesis:

This research focuses on the basics of knowing about the consumer's needs through the factors that influence shopper's decision-making process as it has been unveiled that there lies an important correlation between the profit for the business of each single store and the use of RSs.

FRs makes it easier for customers to quickly make a purchase decision by sorting through the broad variety that is presented in the online store.

Methodology:

The research relied on descriptive approach through the theoretical framework and comparative analysis. It has led to immediate understanding of the practical applications used in the field of digital advertising and how the customer tailored media can be viewed using modern tools and methods. The research provides a systematic approach to facilitate the use of the aforementioned tools. This is usually done by collecting information relating to customers preferences to produce desirable outcomes.

The research conducts qualitative approach for it collects theoretical descriptions, it is used to assess the knowledge collected and describes a framework that can depend on subjective opinions and experiences.

2- Theoretical Framework:

2-1 Artificial intelligence (AI) refers to the simulation of human intelligence in machines that

are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem-solving. (Jake Frankenfield: 2022)

2-1-1 Machine Learning: A branch of artificial intelligence which is broadly defined as the capability of a machine to imitate intelligent human behavior.

2-1-2 Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or infeasible to develop conventional algorithms to perform the needed tasks. Machine learning is closely related to computational statistics (recommendation systems), which focuses on making predictions using computers. (<https://dbpedia.org>)

2-1-1-1 Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain allowing it to "learn" from large amounts of data.

Deep learning eliminates some of data pre-processing that is typically involved with machine learning. These algorithms can ingest and process unstructured data, like text and images, and it automates feature extraction, removing some of the dependency on human experts. (<https://www.ibm.com>) Common deep learning algorithms include convolutional neural networks (CNNs), recurrent neural networks, and deep Q networks.

2-1-1-1-1 The Convolutional Neural Network (CNN) is a class of deep learning which were inspired by biological processes in that the connectivity pattern between neurons resembles the structure of the animal visual cortex. It has shown excellent performance in many computer vision and machine learning problems. CNN is useful in a lot of applications, especially in image related tasks. Applications of CNN include image and video recognition, image classification, image semantic segmentation, recommender systems, object detection in images, etc. (Jianxin WU: 2017)

2-2 An overview of the recommendation system: RSs' technology is built on identifying relationships between people and products based on their profiles. RS is referred to as a decision-making method for users under a multidimensional information environment. A RS has also been described as an e-commerce tool that assists consumers in their search for products by using information about those consumers' preferences and interests. The basic function of a RS is to suggest interesting products or types of items to that a user or consumer may prefer.

There are many definitions of RSs, including:

2-2-1 A tool to mine items and/or collects users' opinions to help users in their search process and suggest items related to their preferences. (Ranjbar kermany, Naime & Alizadeh, Sasan: 2017)

2-2-2 A program or software for content filtering that attempts to reduce the information overload problem, where users encounter a flood of data on the Web, by recommending personalized items to users depending on the items' information and/or users' preferences. (Alqaheri, Hameed and Banerjee, Soumya: 2015)

2-2-3 A system to manage information overload problem by collecting information, guiding users in a personalized way, and providing individualized recommendations as output when there are many

possible alternatives to choose from. (Chen, L., Chen, G. & Wang, F.: 2015)

In a typical RS, people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients. In some cases, the primary transformation is in the aggregation; in others the system's value lies in its ability to make good matches between the recommenders and those seeking recommendations.

2-3 Recommendation system filtering techniques

There have been many different recommendation techniques put out in the fashion industry. The following categories can be used to group these techniques:

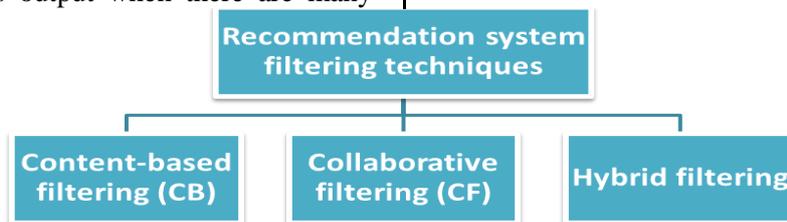


Figure (1) shows Recommendation system filtering techniques

(2-3-1) Content-based filtering recommendation systems (CB) is used to classify users (or consumers) and profile product data according to the properties of the products. This helps in analyzing the characteristics of a recommended fashion item that is utilized to generate predictions. In this technique, user profiles are matched with the inner attributes extracted from the product content (textual description or visual features), which provides the recommendation where the user has

evaluated a specific product in the past. (Chakraborty, Samit: 2021) The product features may be a textual information to describe clothing images or visual features like color, shape, style line, texture, fabric, etc.; while for the users: demographic aspects, surveys answers, etc. A fashion product has various attributes like brand, color, silhouette, shape, texture, etc. these attributes help in finding similarities with other fashion products as shown in figure (2).

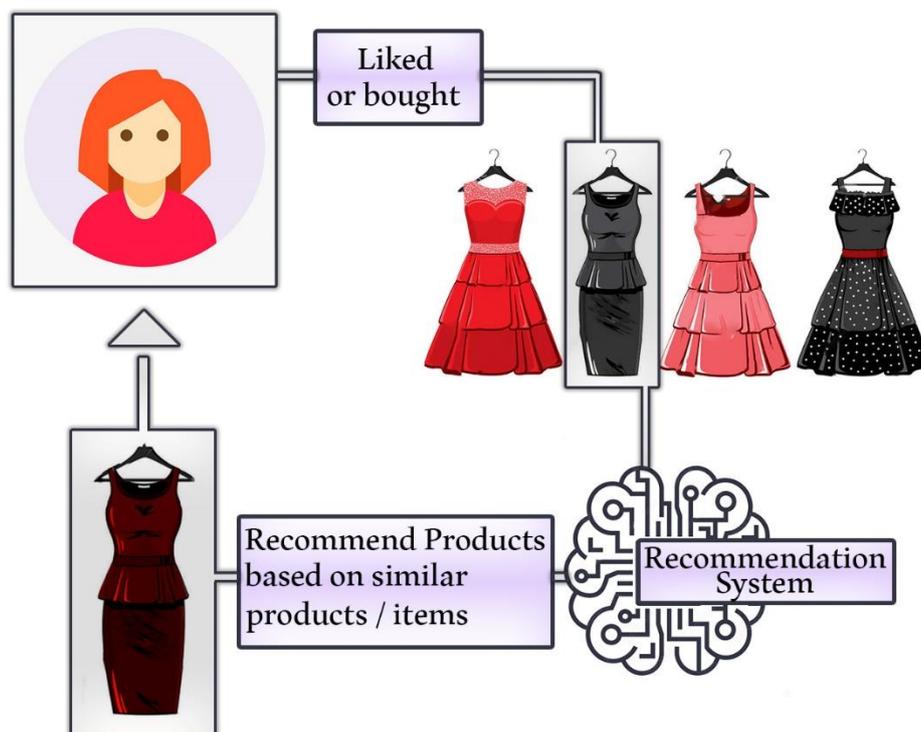


Figure (2) shows CB filtering technique

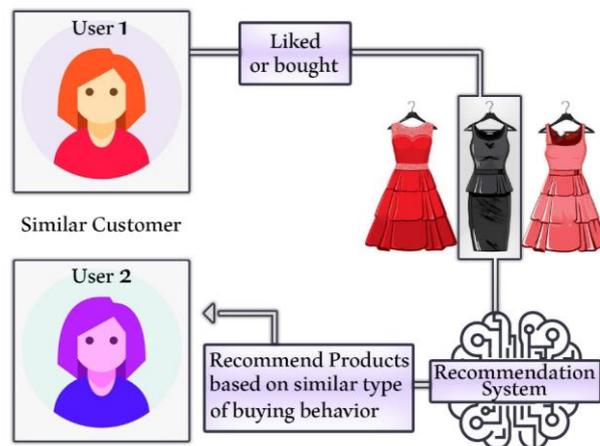
The following steps can be used to summarize the CB filtering approach process:

- **Item representation:** To create the structured item's representation, the item's features are extracted from the item description's information source.
- **Learning the user profile:** A user profile is created based on prior users' actions (i.e., explicit and tacit feedback), such as whether they liked or disliked an item, how they rated it, or how they expressed their thoughts in words (comment).
- **Recommendations' generation:** By matching an item's features to the user's profile, a list of items is suggested to the user. The items that are most likely to appeal to the user are added to the list (i.e. top-ranked items). (AL-Ghuribi, Sumaia, Mohammed a,b and Shahrul Azman Mohd Noah: 2021)

(2-3-2) Collaborative filtering recommendation systems (CF) is a type of WOM marketing and one of the most effective and popular techniques among all of the filtering techniques available for the recommendation system. The CF approach is based on the historical data of user interactions with the products, including explicit (such as user ratings) and implicit input (e.g., purchase, visit, tests). In

collaborative filtering, predictions are generated automatically based on other people's reviews. It formed by leveraging a dataset (user-item matrix) of a group of users' preferences from their ratings for fashion products. It then matches users with relevant interest and preferences by calculating similarities between their profiles to predict to the missing ratings to a different group of users who show similar types of purchase behavior. The mathematical techniques used are the neighborhood method. These users establish a neighborhood. A user receives recommendations for products that he hasn't yet reviewed but that had already received favorable reviews from users in his neighborhood.

As figure (3) shows the rating matrix of user and product interactions, with users as the rows and products as the columns. Rating 5 in this graph denotes the best interaction, while rating 1 denotes the worst interaction. The image also demonstrates how user 2 and user 3 made comparable selections for items (C) and (D), which would lead the CF technique to anticipate that user 3 would engage with item (B) similarly to user 2 and give it a rating of 1 star. In addition, it is how the remaining choices would be entered.



Collaborative Filtering

	A	B	C	D
User 1	5	1	?	?
User 2	?	1	5	?
User 3	?	?	5	1

Figure (3) shows rating matrix of user and product interactions in CF

Amazon.com is an example of e-commerce recommendation engine that uses scalable item to item CF techniques to recommend online products for different users. It uses an explicit information collection technique to obtain information from users. The computational algorithm scales independently of the number of similar users in a segment and items within the database for the purpose of making recommendations. The interface is made up of the following sections, users' browsing history, rating items, and improve users' recommendations and their profile. The system then compares the users browsing pattern on the system and decides the item of interest to recommend to the user. The system matches the user to similar customers based on the items he/she has rated and it predicts users' interests. (Greg Linden, Brent Smith, and Jeremy York: 2003)

2-3-3 Hybrid filtering incorporates multiple RS techniques to improve recommendation performance because other techniques face an issue when there is not enough data to learn the relation

between user and items. In such cases, a hybrid recommendation system, is utilized to develop RSs. There are several ways to implement hybrid recommendation system approaches, such as by merging predictions made using content and CB methods after first generating them independently, or by simply incorporating CF methods' capabilities into content-based CB approaches by a couple of steps: First, add product meta-data—brand, model year, features, etc. Next, add user meta-data—like demographics—to the model (and vice versa). So, the hybrid methods can generate more accurate recommendations. (Rajani Chulyadyo: 2016)

The hybrid filtering technique presumes the results of CB filtering (Recommendation 1) and CF (Recommendation 2), calculates the weights of these results as (Recommendation 3), and then, depending on the weights, influences the higher weighted result to combine the results and recommend the final product (Recommendation 4), which resembles the results of (Recommendation 1) and (Recommendation 2), as shown in figure (4).

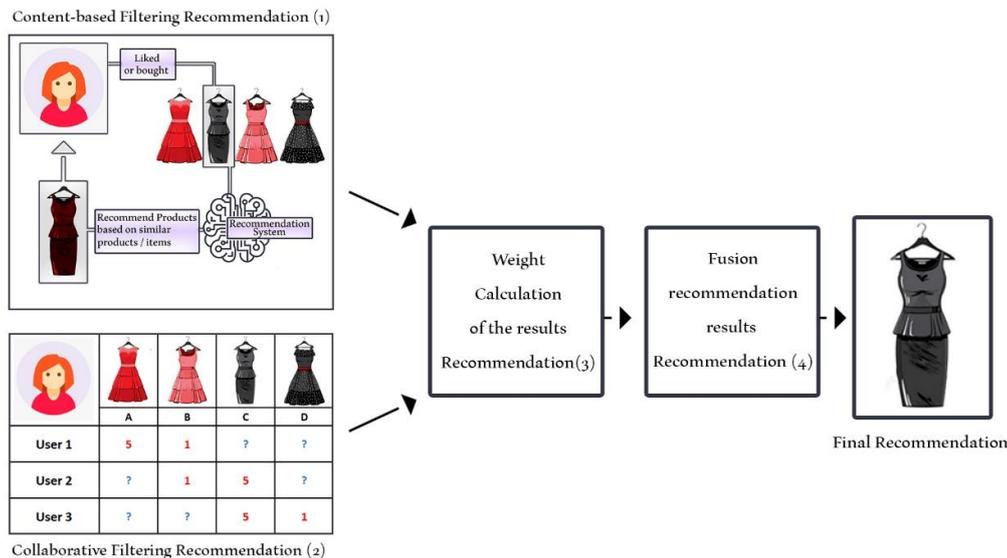


Figure (4) shows Hybrid filtering technique interactions

2-4 Influences of RS Use on Consumer Decision-Making Processes:

Consumer Decision Making refers to the process under which consumers go through in deciding what to purchase. The five phases of the consumer decision-making model are as follows:

- **Problem recognition:** The first and most important stage of the buying process. A customer detects a problem when they notice a considerable gap between their intended state and actual condition in relation to a certain demand or requirement.
- **Information search:** The second stage of consumer decision-making process. When a consumer gets information about products from different sources such as personal, public sources, or past experience.
- **Alternatives evaluation:** This stage comes after the information search, is defined as "the procedures involved in assessing the attractiveness and relative desirability of items, multiple brands, or product and brand qualities." customers may reach a purchase choice at the end of the alternative's evaluation.
- **Purchasing decision:** During this stage, buying behavior turns into action. It influenced by two factors. The first factor is the attitudes of other people related to the consumer. The second factor is unexpected situational factors such as expected price and expected product benefits. (<https://www.iedunote.com>)
- **Post-purchase assessment:** the fifth and last stage of consumer buying decision-making

process. After the use of the product, the customer might be satisfied or dissatisfied, which can influence the other people to buy the product and increase the loyalty of consumer towards the brand. Decision processes usually involve cognitive effort.

Decision effort is usually determined by the decision time and the extent of product search. RS are assumed to be most useful for the decision process in which consumers go through extensive external search and alternative evaluation. The use of RSs saves time for online shoppers. As RSs lighten the burden of screening, narrowing and filtering available alternatives for consumers, consumers have more processing capacity to evaluate alternatives, resulting in better quality decisions. Besides, RSs facilitate the navigation process, making it easier for customer to locate and focus on alternatives that match their preferences. Therefore, RS use is assumed to enhance decision quality. (Phuong, 2021)

2-5 The visual recommendation/ Content-based image retrieval:

The visual FRs are designed to retrieve a ranked list of catalog images similar to the target catalog image. These systems are crucial in helping customers move toward potential buying decisions from recommended products. Catching true correlation between similar product recommendations and user satisfaction will exponentially improve sale experience of companies. One of the major tasks in fashion recommendation systems is accurately finding similar images for a given product image. (Betul Ay, G. Aydin: 2021) Using a content-based filtering technique, the visual recommendation model can directly include visual information into the recommendation objective. The content- Based Image Retrieval technique can find related images from a database with an input image of the content the users' looking for. In essence, a user who is interested in purchasing a specific item on the screen would wish to investigate aesthetically similar things before making the final purchase decision making. These might be objects based on visual characteristics like hues, designs, and shapes.

For a visual RS, the retrieval of the top similar instances is divided into the following steps:

- An image enters the system as a search input
- Identify the key elements in each image so that they may be represented as feature vectors, then calculating the distances between images to determine how similar they are. This image

is compared to all of the databases' images or just a segment of them, and a comparison algorithm offers a similarity score to each of them.

- The recommendation system returns the top images with the highest ratings for similarity to query image as an output.

For example, when searching for an image of a fashion influencer wearing a black dress, the search results will return the more images that are visually similar to the image of the fashion influencer based on visual characteristics of the image. The use of an image to search for a particular dress is more descriptive than a text query and sometimes essential because only in this way it is possible to convey some kind of information that cannot be expressed by words or when the user is not even aware of some particular key details necessary to make a suitable query. (A Nodari: 2012)

Content-based image retrieval also used **computer vision** algorithms for object recognition and to extract other visual information.

2-5-1 Computer vision is a field of artificial (AI) that enables computers and systems to derive meaningful information from digital images, videos and other visual inputs — and take actions or make recommendations based on that information. If AI enables computers to think, computer vision enables them to see, observe and understand. (<https://www.ibm.com>)

Computer vision for fashion has attracted significant attention, with various applications typically built on top of deep CNN. Clothing 'parsing' is one such application, which seeks to parse and categorize garments in a fashion image. Since clothing has fine-grained style attributes (e.g. sleeve length, color distribution and clothing pattern, etc.), some works seek to identify clothing attributes, and detect fashion landmarks (e.g. sleeve, collar, etc.). (J. Jia: 2016)

ASOS, one of the biggest names in fashion e-commerce, is rolling out its Style Match visual search tool globally for iOS and Android. the feature lets users take or upload a photo to the app to find visually similar clothing styles that are available to shop.

Users can upload an Instagram screenshot, a magazine photo, or a photo they took directly from the app by tapping the camera icon in the search box. This rollout from ASOS then, aims at enabling shoppers to capture fleeting moments – whether that's someone they pass on the street, a look a friend is wearing or even a screengrab – and use them to search through the site's product lines and the results will include similar shoppable items as shown in figure (5).

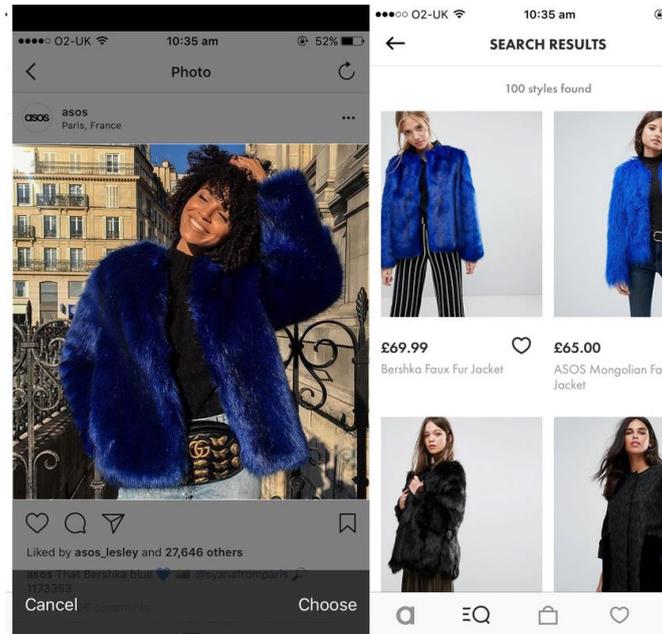


Figure (5): ASOS' style match for visual recommendation (<https://www.theverge.com>)

2-6 Style recommendation:

A primary role of an online FRs is to establish correlations between clothing items to assist users in finding functionally complementary or aesthetically pleasing outfits. Users often buy the clothing which meets their visual preference and fashion style consistency between clothing items has a huge impact on user decision making.

In the fashion domain, visual features can be useful to determine compatibility between items for example, the former setting takes a fashion item as a query and seeks to recommend compatible items from different categories, given a top (or any upper garment), the system suggest a list of bottoms (such as pants or skirts) from a big collection that best complement the top, and vice versa (Deldjoo et al.:2022) as figure (6) shows.

So, the main challenge in this discipline is to figure out how to assess distinguishing characteristics for many styles and also discover what style creates a trend.

In order to improve the performance of recommending compatibility modelling among fashion items, the system must analyze and extract

discriminative features for different styles by combining the visual understanding of fashion item (color, texture, material, pattern and shape) and contextual modalities (e.g., title and category) of clothing. Visual matching requires modeling a human notion of the compatibility between fashion items, which involves matching features such as color and shape etc.

Apparel manufacturers have employed a convolutional neural network (CNN) to tackle various difficulties on their e-commerce sites, including clothing recognition, extracting visual features of outfits, search, and suggestion. Then, they devise a personalized fashion design system based on the learned CNN and user representations. Such systems are focused on comparison and retrieval, rather than personalized recommendation to learn notions of 'style'.

Some studies propose a pre-trained RS for clothing coordinates using full-body photographs from fashion magazines. Other studies describe a visual RS for street fashion images through color modeling.



Figure (6): Some results with fashion style consistency obtained by our SCNN model (Sun, GL.: 2018)

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Some studies propose a pre-trained RS for clothing coordinates using full-body photographs from fashion magazines. Other studies describe a visual RS for street fashion images through color modeling. There is an advanced RS that learns clothes knowledge rather than tracking customer

data. In research, based on a comprehensive review and latest updates, it is found that some recent studies have started to focusing on the integration of clothing and fashion knowledge. The development of apparel data sets is based on the specific theories identified in clothes and fashion basics, which are the clothes communication and semiotics theories describing the relationship between clothes and people. The structure of apparel datasets is connected with the clothes communication networks composed of three major components, including apparel signs, denotation meanings and connotation meaning.

The first order represents raw apparel image data set which refer to the visual signs of clothing such as visual elements of line, shape, volume, drape and other elements in the listed. The second order is an ATTRIBUTE data set represents the denotation meanings of clothes that indicate apparel label lines, shapes, the contrast of color schemes, patterns and other design features. The third order is MEANING labelling data set represents the connotation meanings outside of clothes which denote the feelings, thoughts, beliefs and desires of clothes that are generated by the mental concept of people. For example, Vertical lines create a sense of lengthiness and elegance as they lead the eyes to view the body in an up-and-down motion, as shown in figure (7). (Congying Guan et al.:2018)

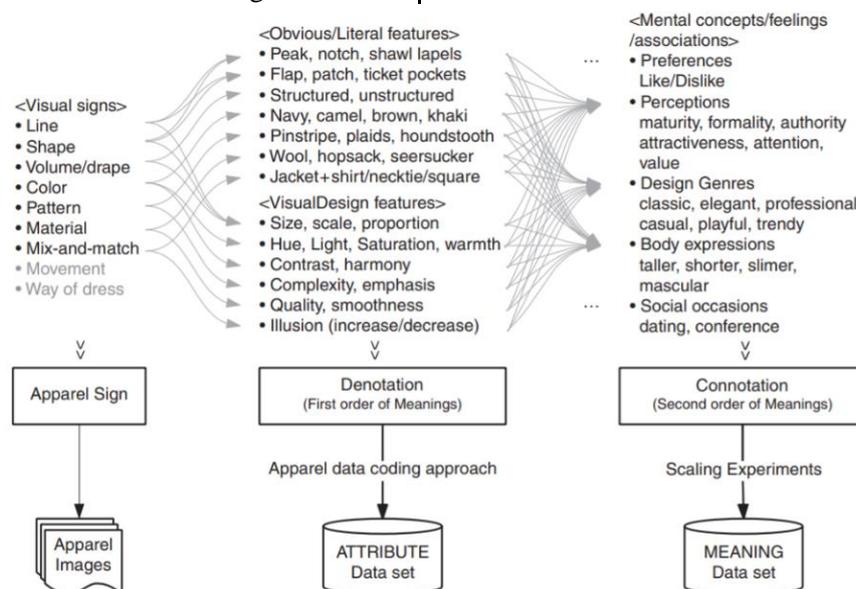


Figure (7) shows Apparel communication networks and data definitions (Congying Guan, Shengfeng Qin: 2019)

2-7 Size recommendation:

Personalized size and fit recommendations bear crucial element for any fashion e-commerce sector in addition to style preference. In comparison with brick and mortar stores, there is no physical fashion product to examine and test in an online experience. The main factors influencing a consumer's purchase

decision are the product's photos, description, and sizing charts, to make matters worse, the notion of size is intrinsically ambiguous: for instance, size charts may be vaguely defined (e.g. 'Small', 'Medium', 'Large'), they may differ between regions (e.g., EU vs. US sizes), or across brands. (Abdul-Saboor Sheikh et al.: 2019) For instance, a

Calvin Klein T-shirt of size M has chest measurement of 40 inches while a Tommy Hilfiger T-shirt of size M has a chest measurement of 38 inches. Additionally, even for a same brand, different product lines and various fits (Slim, Regular etc.) makes choosing size a tricky process. (G Mohammed Abdulla & Sumit Borar: 2017)

Due to this gap, a significant percentage of returns from online purchasing are caused by poor sizing and fit. That's why, there are competing applications with various approaches for size recommendation has appeared.

Size recommendation tools are emerging as a common way to reduce the returns of fashion items. Correct fit prediction increases customer satisfaction and benefits the company by lowering expenses associated with size-related returns.

2-7-1 Definition of size recommendation tool:

Size recommendation tools are digital solutions that analyze each customer's unique body and fit preferences to provide personalized advice on which size a customer should buy.

2-7-2 Types of size recommendation tools:

- **Photo/video-based solutions application:** which uses photo scanning of customer's body to extract accurate measurement data and body type analysis for custom fit applications, and then compare against fashion product details by AI technology. (<https://mysizeid.com>) Several reports suggested that scanners achieve accuracies results. Another advantage of using scanners is the measurement speed, the duration of an automatic scan is often under few seconds and may go up to 30 seconds for high-quality scans. (BARTOL. Kristijan et al.: 2016) Modern scanning solutions require the customer to snap photos using their smart phone device such as (3DLOOK) or (Mysize) application.
- **Quiz-based solutions:** The majority of size

recommendation applications entail answering a few simple questions, the responses to which help calculate customers' measurements and recommend the closest standard size like (easysize.me), (sizebay), (Asos) and etc. Customers are asked to enter their height, weight, shoulder shape, age, fit preference, and preferred brands and sizes. This data is fed into an algorithm, which compares the information provided against product data to determine the size that best meets the customer's needs. See figure (8)

- **Purchase analysis solutions:** This rely on customer's previous purchases analysis. By comparing the product data of customer's garment preferences versus the products they're interested in buying. Using CF recommendation, the algorithm works on actual sales data from the retailer of that garment in order to adjust the size charts tracks trends in consumer purchasing and returns behavior.
- **Review analysis solutions:** This solution uses data provided in reviews from other customers that have purchased the same product and their opinion on its fit. Each garment item page provides information on whether the item is too small, just right, somewhat large, or excessively large, as well as advice on whether shoppers should get their regular size, a smaller size, or a larger size.

It uses hybrid filtering recommendations to combine both interaction data with arbitrary customer and item attributes for personalized size and fit prediction. Standard CF techniques only use interaction data to simulate consumer behavior. (<https://3dlook.me>)

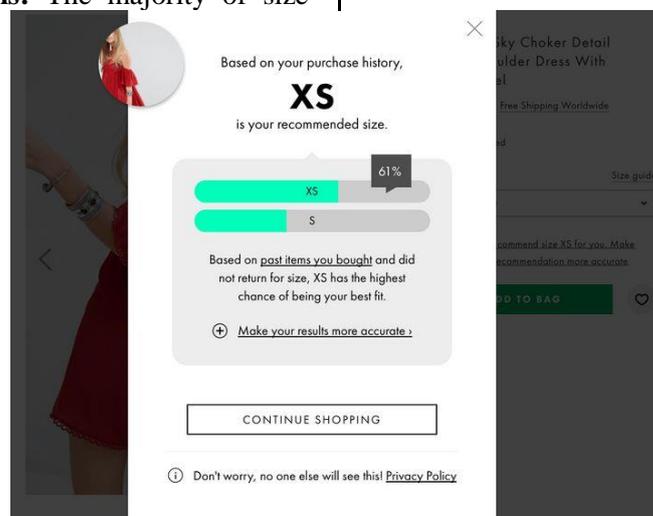


Figure (8): Asos size recommendation tool based on consumers' past purchase history and returns (<https://www.huffingtonpost.co.uk>)

3- Conclusion:

The research work puts forward a comparative analysis of various recommendation filtering techniques different application fields, techniques used, simulation tools used, datasets used, and different RS features in fashion arena which will benefit both consumers and retailers soon. This paper discussed the two traditional recommendation techniques and highlighted their strengths and challenges with diverse kind of hybridization strategies used to improve their performances. RSs have the potential to open up new options for retailers by allowing them to generate tailored suggestions to consumers based on information obtained from the Internet. E-commerce platforms when powered with personalized RSs can help increase customer clicks and purchases for the given online retailer. They assist consumers in quickly locating items and services that closely match their preferences. Product attributes and clothing style matching are common features of CB and CF techniques. In order to create a useful RS, further study should focus on integrating precise product picture classification based on variations in color, trend, and apparel style. According to our study, there are now available applications that purport to let customers scan items of apparel and accessories to provide outfit recommendations. Through a variety of applications, customers might also get suggestions based on their purchasing behavior and clothing needs. Other applications use this technology to recommend based on size or fitting, similarly to an in-store human fitting room assistant. Overall, this paper provides researchers with insight and future direction on RSs.

4- Results:

- RSs overcome the limitations of e-commerce services, as RSs share core values with consumer decision support systems, they promote personalization and encourage consumer decision making on e-commerce websites rather than feeding them with suggestions.
- RS use saves time for online shoppers and improves consumer decision quality.
- Retailers can gather information about customers' past purchases and product ratings from the RS and use it to anticipate trends for upcoming seasons.
- Deep learning techniques should be utilized more frequently to swiftly examine clothing from many web databases and deliver timely suggestions to users or customers.
- The findings indicate that RSs performance expectancy is an important factor influencing consumers' purchase intention, and that recommendation accuracy, novelty, and

diversity indirectly influence purchase decision making by shaping consumers' perceptions of RS performance expectancy.

- There are various RS phases to filter information about the consumer's liking for a product through the Internet such as content-based filtering, collaborative filtering and hybrid filtering. These data can be gathered in the forms of voting, tagging, reviewing and the number of likes or dislikes provided by the user. It may also include reviews written in blogs, videos uploaded on YouTube or messages about a product. Then, preferences are expressed in the form of numerical values.
- The visual recommendation (content-based image retrieval) is an excellent strategy to utilize in the second stage of purchasing decision process, which focuses on gathering information.
- Fashion style recommendation system generates new solutions by finding the most relevant combination of all basic garment elements, which can be easily evaluated by non-professional consumers.
- The use of a size suggestion tool is an efficient way for both e-commerce customers and retailers, for customers: to get the right size clothing and avoid the difficult effort of browsing size charts while making an online purchase, and for retailers: It solves the problem of losing a lot of money as a result of a high percentage of product returns owing to size and fit mismatches..

5- Recommendations:

- Researchers can create more advanced filtering methods by considering the relationship between customer personalities and apparel preferences.
- The quality of the images has always been a key problem for recommendation engines. Product retrieval and prediction accuracy is greater when product photos are shot in controlled surroundings. Selfies and other images shot in ad hoc settings, however, present problems for the algorithm and produce unreliable forecasts. In order to grasp product features and human postures, which are used to forecast consumers' fashion preferences, more research on image parsing is thus needed.
- Encourage additional research and study on the efficiency of the fashion suggestion system approach because it is still a new technology with potential for increased employment.
- The necessity of considering consumer's body shape in recommending items that fits them.

- Retailers can combine online and offline purchase data to help predict customer preferences and get accurate recommendations.

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