Fashion Recommendation Systems

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Image-based fashion recommendation systems (FRSs) have attracted a huge amount of attention from fast fashion retailers as they provide a personalized shopping experience to consumers. With the technological advancements, this branch of artificial intelligence exhibits a tremendous amount of potential in image processing, parsing, classification, and segmentation.

fashion recommendation system | e-commerce | filtering techniques | algorithmic models | performance

1. Introduction

Clothing is a kind of symbol that represents people's internal perceptions through their outer appearance. It conveys information about their choices, faith, personality, profession, social status, and attitude towards life. Therefore, clothing is believed to be a nonverbal way of communicating and a major part of people's outer appearance [1]. Recent technological advancements have enabled consumers to track current fashion trends around the globe, which influence their choices [2][3]. The fashion choices of consumers depend on many factors, such as demographics, geographic location, individual preferences, interpersonal influences, age, gender, season, and culture [4][5][6][7][8]. Moreover, previous fashion recommendation research shows that fashion preferences vary not only from country to country but also from city to city [9]. The combination of fashion preferences and the abovementioned factors associated with clothing choices could transmit the image features for a better understanding of consumers' preferences [7]. Therefore, analyzing consumers' choices and recommendations is valuable to fashion designers and retailers [9][10][11]. Additionally, consumers' clothing choices and product preference data have become available on the Internet in the form of text or opinions and images or pictures. Since these images contain information about people from all around the world, both online and offline fashion retailers are using these platforms to reach billions of users who are active on the Internet [10][12][13]. Therefore, e-commerce has become the predominant channel for shopping in recent years. The ability of recommendation systems to provide personalized recommendations and respond quickly to the consumer's choices has contributed significantly to the expansion of e-commerce sales [14].

According to different studies, e-commerce retailers, such as Amazon, eBay, and Shopstyle, and social networking sites, such as Pinterest, Snapchat, Instagram, Facebook, Chictopia, and Lookbook, are now regarded as the most popular media for fashion advice and recommendations [15][16][17][18][19][20][21][22]. Research on textual content, such as posts and comments [23], emotion and information diffusion [24], and images has attracted the attention of modern-day researchers, as it can help to predict fashion trends and facilitate the development of effective recommendation systems [5][25][26][27]. An effective recommendation system is a crucial tool for successfully conducting an e-commerce business. Fashion recommendation systems (FRSs) generally provide specific recommendations to the consumer based on their browsing and previous purchase history. Social-network-based FRSs consider the user's social circle, fashion product attributes, image parsing, fashion trends, and consistency in fashion styles as important factors since they impact upon the user's purchasing decisions [28][29][30][31][32][33][34][35][36][37][38]. FRSs have the ability to reduce transaction costs for consumers and increase revenue for retailers. With the exception of a single study from 2016 that focuses only on apparel recommendation systems [10], no current research presents recent advances in research on fashion recommendation systems. Therefore, the purpose of this paper is to present an integrative review of the research related to fashion recommendation systems. Moreover, Guan et al. cited research published until 2015. Therefore, the first objective of this paper is to review the most recent research published on this topic from 2010 to 2020. The previous study did not provide an in-depth analysis of the computational methods or algorithms corresponding to the fashion recommendation systems. This review study aims to fulfill this research gap and rigorously study the principles underlying, the methods used by, and the performance of the state-of-the-art fashion recommendation systems. To the best of our knowledge, this in-depth study is first of its kind. It includes research articles related to image parsing, clothing and body shape identification, and fashion attribute recognition, which are critical parts of fashion recommendation systems (FRSs). This review paper also provides a guideline for a research methodology to be used by future researchers in this field. The first section of this review discusses the history and background of FRSs. The second section presents a concise history and overview of recommendation systems. The third section aims to integrate the scholarly articles related to FRSs published in the last decade. The fourth section defines the metrics that are used by researchers to present and discuss recommendation results. The fifth section forms the major part of this review and focuses on various FRSs followed by different computational algorithmic models and recommendation filtering techniques used in fashion recommendation research. It will help researchers to understand these crucial parts of a FRS. The final section highlighted the existing challenges of using state-of-the-art recommendation systems followed by providing recommendations to overcome them and proposing a novel FRS based on the research findings discussed in section five. The study of the existing literature revealed that fashion recommendation systems have a huge impact on consumers' buying decisions. Hence, fashion retailers and researchers are exploring and developing state-of-the-art recommendation models to improve the accessibility, navigability and consumers' overall purchasing experience. One of the prime elements that has been continuously researched in these articles was the improvement of existing and the development of new algorithms relevant to the filtering techniques [4][15][33][39][40][41][42][43][44][45][46][47][48][49][50][51] (**Figure 1**).

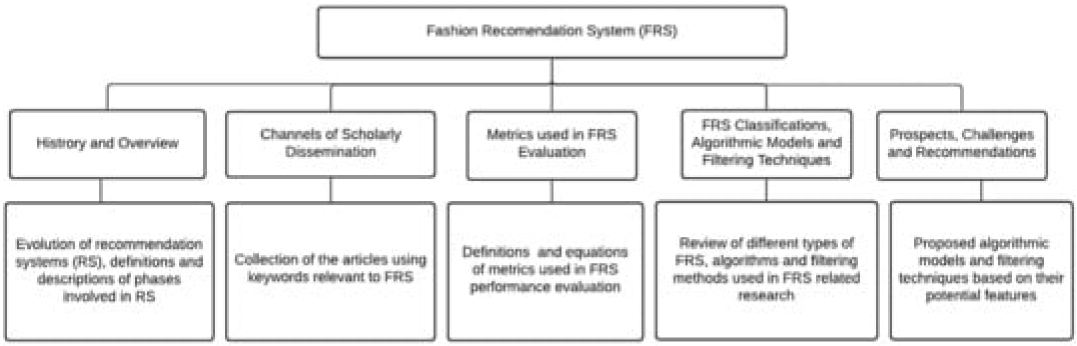

Figure 1. Organizational structure of the article.

2. History and Overview of Recommendation System

The era of recommendation systems originally started in the 1990s based on the widespread research progress in Collective Intelligence. During this period, recommendations were generally provided to consumers based on their rating structure [52]. The first consumer-focused recommendation system was developed and commercialized by Goldberg, Nichols, Oki and Terry in 1992. Tapestry, an electronic messaging system was developed to allow users only to rate messages as either a good or bad product and service [53]. However, now there are plenty of methods to obtain information about the consumer's liking for a product through the Internet. These data can be retrieved in the forms of voting, tagging, reviewing and the number of likes or dislikes the user provides. It may also include reviews written in blogs, videos uploaded on YouTube or messages about a product. Regardless of communication and presentation, medium preferences are expressed in the form of numerical values [52][54]. **Table 1** presents the history of the progress of fashion recommendation systems over the last few decades.

Table 1. History of recommendation systems; produced by the authors based on [52][55][56].

Year	Recommendation System Approach	Properties
Before 1992	Mafia, developed in 1990	• Content filtering. • Mail filtering agent for providing a cognitive intelligence-based service for document processing.
1992 to 1998	Tapestry, developed in 1992	• Collaborative filtering. • Developed by Palo Alto. • Allowed users only to rate messages as either good or bad

Year	Recommendation System Approach	Properties
		product and service.
	Grouplens, first used in 1994	• Rate data to form the recommendation.
	Movielens, proposed in 1997	• Useful to construct a well-known dataset.
1999 to 2005	PLSA (Probabilistic Latent Semantic Analysis), proposed in 1999	• Developed by Thomas Hofmann. • Collaborative filtering.
2005 to 2009	Several Latent Factor Models such as Singular Value Decompositions (SVD), Robust Singular Value Decomposition (RSVD), Normalized Singular Value Deviation (NSVD).	• Collaborative filtering approach. • Find out factors from rating patterns.
2010 to onwards	Context-aware-based, instant-personalization-based	• Combined techniques of content and collaborative approach.

However, implementation was mostly in the development stage until 2007–2008 [10][52][55][57][58][59]. As with other products such as electronics and books, fashion products were also recommended based on the user's previous purchase history. With the continuous progress in computer vision algorithms, personalized recommendations utilizing personal factors and user reviews have become more popular today [10][58][60].

3. Channels of Scholarly Dissemination Related to Fashion Recommendation System (FRS)

Articles published from January 2010 to June 2020 have been considered for the review purpose of this article. Various online literature resources or databases such as Scopus, Web of Science, Science Direct, and Design and Applied Arts Index (DAAI) have been used to find the literature. Boolean operator techniques i.e., "AND" or "OR" strategies were used to search articles from these sources. Keywords grouped in three categories as listed below were used to conduct the final search.

Group 1: Fashion OR Style OR Apparel OR Clothing.

Group 2: Recommend*.

Group 3: Filtering Technique OR Algorithm OR Model OR Artificial Intelligence OR Neural Network OR Deep Learning OR Meta-Learning OR Fuzzy Techniques OR Model OR Image Processing OR Image Retrieval OR Image Feature extraction.

Final Search = Group 1 AND Group 2, Group 1 AND Group 2 AND Group 3.

Overall, 230 scholarly articles and 9 web sources have been reviewed. Among these, 214 scholarly articles were found containing the required keywords when using the search strategy mentioned above. Among these, 132 articles are indexed in Scopus, 26 in Web of Science, 3 in Science Direct and 1 in the Design and Applied Arts Index (DAAI) database. In addition, 50 articles and 2 patents were found in Google Scholar, published in different peer-reviewed journals and conferences.

4. Metrics Used in Fashion Recommendation System Evaluation

The performance of a recommendation algorithm is evaluated by using some specific metrics that indicate the accuracy of the system. The type of metric used depends on the type of filtering technique. Root Mean Square Error (RMSE), Receiver Operating Characteristics (ROC), Area Under Cover (AUC), Precision, Recall and F1 score is generally used to evaluate the performance or accuracy of the recommendation algorithms.

Root-mean square error (RMSE). RMSE is widely used in evaluating and comparing the performance of a recommendation system model compared to other models. A lower RMSE value indicates higher performance by the recommendation model. RMSE, as mentioned by [61], can be as represented as follows:

$$RMSE = \sqrt{\frac{1}{N_p}\sum_{u,i}(p_{ui} - r_{ui})^2} \qquad (1)$$

where, N_p is the total number of predictions, p_{ui} is the predicted rating that a user u will select an item i and r_{ui} is the real rating.

Precision. Precision can be defined as the fraction of correct recommendations or predictions (known as True Positive) to the total number of recommendations provided, which can be as represented as follows:

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)} \qquad (2)$$

It is also defined as the ratio of the number of relevant recommended items to the number of recommended items expressed as percentages.

Recall. Recall can be defined as the fraction of correct recommendations or predictions (known as True Positive) to the total number of correct relevant recommendations provided, which can be as represented as follows:

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\,(TP) + False\ Negative\ (FN)} \tag{3}$$

It is also defined as the ratio of the number of relevant recommended items to the total number of relevant items expressed as percentages.

F1 Score. F1 score is an indicator of the accuracy of the model and ranges from 0 to 1, where a value close to 1 represents higher recommendation or prediction accuracy. It represents precision and recall as a single metric and can be as represented as follows:

$$F1\ score = 2 \times \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Coverage. Coverage is used to measure the percentage of items which are recommended by the algorithm among all of the items.

Accuracy. Accuracy can be defined as the ratio of the number of total correct recommendations to the total recommendations provided, which can be as represented as follows:

$$Accuracy = \frac{TP + FN}{TP + FN + TN + FP} \tag{5}$$

Intersection over union (IoU). It represents the accuracy of an object detector used on a specific dataset [62].

$$IoU = \frac{TP}{TP + FN + FP} \tag{6}$$

ROC. ROC curve is used to conduct a comprehensive assessment of the algorithm’s performance [57].

AUC. AUC measures the performance of recommendation and its baselines as well as the quality of the ranking based on pairwise comparisons [5].

Rank aware top-N metrics. The rank aware top-N recommendation metric finds some of the interesting and unknown items that are presumed to be most attractive to a user [63]. Mean reciprocal rank (MRR), mean average precision (MAP) and normalized discounted cumulative gain (NDCG) are three most popular rank aware metrics.

MRR. MRR is calculated as a mean of the reciprocal of the position or rank of first relevant recommendation [64][65]. MRR as mentioned by [64][65] can be expressed as follows:

$$MRR = \frac{1}{N_u} \sum_{u \in N_u} \frac{1}{L_u^n [k] \in R_u} \tag{7}$$

where u, N_u and R_u indicate specific user, total number of users and the set of items rated by the user, respectively. L indicates list of ranking length (n) for user (u) and k represents the position of the item found in the he lists L.

MAP: MAP is calculated by determining the mean of average precision at the points where relevant products or items are found. MAP as mentioned by [65] can be expressed as follows.

$$MAP = \frac{1}{N_u \, |R_u|} \sum_{k=1}^{n} \mathbb{1} \left(L_u^n [k] \in R_u \right) P_u @ k \tag{8}$$

where P_u represents precision in selecting relevant item for the user.
NDCG: NDCG is calculated by determining the graded relevance and positional information of the recommended items, which can be expressed as follows [65].

$$NDCG_u = \frac{\sum_{k=1}^{n} G\,(u, n, k) D\,(k)}{\sum_{k=1}^{n} G^*\,(u, n, k) D\,(k)} \tag{9}$$

where D (k) is a discounting function, G (u, n, k) is the gain obtained recommending an item found at k-th position from the list L and G^* (u, n, k) is the gain related to k-th item in the ideal ranking of n size for u user.

5. Fashion Recommendation System (FRS), Algorithmic Models and Filtering Techniques

FRS can be defined as a means of feature matching between fashion products and users or consumers under specific matching criteria. Different research addressed apparel attributes such as the formulation of colors, clothing shapes, outfit or styles, patterns or prints and fabric structures or textures [10][58][66][67]. Guan et al. studied these features using image recognition, product attribute extraction and feature encoding. Researchers have also considered user features such as facial features, body shapes, personal choice or preference, locations and wearing occasions in predicting users' fashion interests [31][67][68][69][70]. A well-defined user profile can differentiate a more personalized or customized recommendation system from a conventional system [28][71]. Various research projects on apparel recommendation systems with personalized styling guideline and intelligent recommendation engines have been conducted based on similarity recommendation and expert advisor recommendation systems

[10][58][72]. Image processing, image parsing, sensory engineering, computational algorithms, and computer vision techniques have been extensively employed to support these systems [32][73][74][75][76][77].

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