LITERATURE SURVEY

- OBJECTIVE

The growing number of fashion e-commerce digital platforms, customers can see and choose from a massive number of virtual fashion products merchandised virtually. There has been a dramatic shift in customers' purchasing behaviour, which is impacted by several factors, such as social media, fashion events, and so forth. Consumers now increasingly prefer to select their products from the immense pool of options and want them to be delivered in a very short time. It is challenging for fashion retailers to fulfil consumer demands in a short time interval. Therefore, it is crucial for fashion apparel retailers to make efficient and quick decisions concerning inventory replenishment in advance based on the forecast of future demand patterns.
The textile and apparel industries have grown tremendously over the last years. Customers no longer have to visit many stores, stand in long queues, or try on garments in dressing rooms as millions of products are now available in online catalogues. However, given the plethora of options available, an effective recommendation system is necessary to properly sort, order, and communicate relevant product material or information to users. Effective fashion RS can have a noticeable impact on billions of customers' shopping experiences and increase sales and revenues on the provider-side. The goal of this survey is to provide a review of recommender systems that operate in the specific vertical domain of garment and fashion products. We have identified the most pressing challenges in fashion RS research and created a taxonomy that categorizes the literature according to the objective they are trying to accomplish (e.g., item or outfit recommendation, size recommendation, explainability, among others) and type of side-information (users, items, context). We have also identified the most important evaluation goals and perspectives (outfit generation, outfit recommendation, pairing recommendation, and fill-in-the-blank outfit compatibility prediction) and the most commonly used datasets and evaluation metrics.

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- OVERVIEW

In recent years, the textile and fashion industries have witnessed an enormous amount of growth in fast fashion. On e-commerce platforms, where numerous choices are available, an efficient recommendation system is required to sort, order, and efficiently convey relevant product content or information to users. With technological advancements, this branch of artificial intelligence exhibits a tremendous amount of potential in image processing, parsing, classification, and segmentation. Despite its huge potential, the number of academic articles on this topic is limited.The available studies do not provide a rigorous review of fashion recommendation systems and the corresponding filtering techniques. To the best of the authors' knowledge, this is the first scholarly article to review the state-of-the-art fashion recommendation systems and the corresponding filtering techniques. In addition, this review also explores various potential models that could be implemented to develop fashion recommendation systems in the future. This paper will help researchers,academics, and practitioners who are interested in machine learning, computer vision, and fashion retailing to understand the characteristics of the different fashion recommendation systems.

Keywords: fashion recommendation system, e-commerce, filtering techniques,algorithmic models,performance.

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]. Research on textual content, such as posts and comments, emotion and information diffusion, 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. 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. 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, 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.

Recommendation System

Recommendation system (RS) is referred to as a decision-making approach for users under a multidimensional information environment. RS has also been defined as an e-commerce tool, which helps consumers search based on knowledge that is related to a consumer's choices and preferences. RS also assists in augmenting social processes by using the recommendations of other users when there is no abundant personal information or knowledge of the alternatives . RS handles the complication of information overload that consumers usually encounter by offering customised service, exclusive content, and personalised recommendations. There are multiple phases involved in the recommendation system that develop the foundation of any state-of-the-art recommendation system. These are defined as the information collection phase, the learning phase, and the recommendation phase.The interrelationship of these phases involved in the recommendation process. It shows that information collection is the initial stage of RS, which is followed by the learning phase and the recommendation phase. The recommendation provided in the last phase can be generated based on information gathered during the information collection phase.

Recommendations can also be provided by combining the learned information with the rating matrix to recommend learning resources]. Researchers reported improved recommendation accuracy using hybrid models in comparison with product content-based or other user preference-based collaborative models. 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.

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, can be as represented as follows:

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

where, Np is the total number of predictions, pui is the predicted rating that a user u will select an item i and rui 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:

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

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 .

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

ROC. ROC curve is used to conduct a comprehensive assessment of the algorithm's performance
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. 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 MRR as mentioned by 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, Nu and Ru 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 can be expressed as follows.

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

where Pu 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].

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

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.
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. 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. A well-defined user profile can differentiate a more personalised or customised recommendation system from a conventional system. 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. Image processing, image parsing, sensory engineering, computational algorithms, and computer vision techniques have been extensively employed to support these systems.

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