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Personalized content recommendations on smart TV: Challenges, opportunities, and future research directions

Iftikhar Alam, Shah Khusro *, Mumtaz Khan

Department of Computer Science, University of Peshawar, Peshawar, Pakistan

A R T I C L E I N F O

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A B S T R A C T

Web recommender systems play a significant role in different domains, such as movies, books, music, etc., and contributes to not only user satisfaction but also to e-business and e-commerce. It utilizes the user's profile information, preferences, and activities for recommendations of different objects. However, the distinct nature of watching smart TV greatly affects the accuracy and efficiency of recommender systems due to the reasons that it is a lean-back and multi-user device. Hence, the predictions and calculations of a user's profile, preferences, and activities cannot be accurately utilized by the recommender systems for recommendations to the exact viewer(s) watching smart TV. This paper presents a critical review of existing recommender systems in the perspectives of smart TV watching scenarios. It highlights the issues and challenges and presents some research opportunities to deal with it. It further presents a subjective study for validating the highlighted factors that affect the recommendation results specifically on a smart TV. Results show that watching activities on a smart TV is significantly different from other devices, such as smartphones and computers. It further shows that smart TV is a non-personalized device and normally enjoyed in groups. Hence, personalized recommendations on smart TV need further investigation. The paper concludes that the existing recommender systems need further improvement to cope with issues of recommendations on a non-personalized device i.e., smart TV. Improving the recommender system for smart TVs may contribute not only to the viewer's satisfaction but also to the conversion rate.

1. Introduction

The huge and unstoppable growth of information and multimedia content over the Web makes it difficult to find the desired items and hence create the issue of cognitive overload. To mitigate this issue, different techniques have been used, such as web directories, search engines, and recommender systems, etc. The recommender systems are also used to overcome the information overload and helpful in a situation where we intend to recommend an item from a massive collection of items [1,2]. A recommender system is a software tool that recommends suitable items, such as channels, video, clips, ads, apps, games, etc., to a user [2]. They are deployed on the Web that helps a user in selecting the items of interest [3–5]. The recommender system takes different parameters, such as profile information, watching history, demographics, location, etc., as input and recommend the items that are supposed to be relevant to a user [4,6,7]. However, the predictions and calculations for building a user profile on a smart TV are not always accurate due to the reasons that smart TV is a lean back, shared, and multi-users device.

Web content can be enjoyed on a smart TV. It is becoming a pervasive computing device by merging the traditional TV systems with computing, connectivity, and smart capabilities [8,9]. The birth of this new TV brings issues and challenges in the form of security, privacy, personalized recommendations, interactivity, inconsistent updates of software/hardware, etc. The security of viewers is more vulnerable when a smart TV is connected to the public network, i.e., internet [9–13]. In most of the households, smart TV is enjoyed in groups that create issues in personalized content recommendations not only to a single viewer but also to the group of viewers. The interactive nature of a smart TV is welcome by the viewers, but interaction beyond a limit may affect the unique feature, i.e., the lean back mode of TV [8]. In the lean-back mode, the contents are enjoyed in passive mode [14]. Moreover, browsing and searching for the desired content in a smart TV is not only time-consuming but also difficult due to the limited functionalities of widely used legacy remote-controls [15]. The Electronic Program Guides (EPGs) are available for channel searching; however, due to a large number of channels, scrolling and searching become a difficult job [16]. The smart TV is more interactive than a conventional legacy TV system but still enjoyed as a lean-back device, preferably less interactive

* Corresponding author.
E-mail addresses: iftikharalam@uop.edu.pk (I. Alam), khusro@uop.edu.pk (S. Khusro), mumtaz.ksu@uop.edu.pk (M. Khan).

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and passive as legacy TV systems [17]. Besides, social metadata, such as tagging, likes/dislikes, and comments, gives better intimations for recommender systems [18]. Besides full support, socialization is a rare activity on a smart TV. Being a connected device, activities such as clicks, navigations, queries, etc., may enhance recommendation results. However, the approaches for analyzing user activities, such as data mining, clickstream analysis, and in-depth identification of a viewer(s), may lead to serious security and privacy threats [17]. The security and privacy threats make such data analysis approaches inefficient for smart TV viewers. The watching behavior and watching distance on smart TV affect the recommendations on a smart TV[19]. For example, most of the smart TVs are used for streaming live channels and movies. Therefore, navigating between channels, movies, and videos may provide limited information for recommender systems. In this case, we have a few implicit feedbacks that may provide limited inputs to a recommender system [20].

The existing recommender systems have many success stories, especially in the field of e-commerce and e-business, and work significantly for computers and smartphone users [21]. It uses different approaches, such as content-based filtering approach, collaborative filtering approach, or hybrid. The content-based approach relies on profile information and content with an item. The collaborative filtering approach relies on similar profiles in a circle (*see Section 3.4.1 for more details*). The hybrid approach combines both for generating more precise results [22]. In such cases, the existing recommender systems for smart TV have numerous issues (*see section 3*) that creates hurdles in precise and relevant recommendations. For example, most of the existing recommender systems focus on individual user preferences [23]. However, a smart TV can be enjoyed by an entire family or a closed group of viewers. In such cases, the smart TV is considered as a single viewer profile that represents the group(s) of viewers, and hence recommendations may not be relevant to every member of a group. Besides, personalized recommender systems use several parameters, such as location, profile information, watching history, feedbacks, apps on a device, age, etc.,[24]. These parameters are enough for personalized recommendations on computers or smartphones. However, in the case of smart TV watching scenarios, most of such parameters are either impracticable or difficult to predict. Other issues that affect the recommendation process on a smart TV are passive interaction by the viewer and a different watching behavior. The user interaction with a device enriches a user profile and may enhance recommendation results [25]. Besides full support for advanced communication devices, still, the primary device for communicating with a smart TV is the legacy remote control, which makes it difficult to interact with a smart TV for secondary tasks, such as typing, navigation, etc.,[26,27]. Although, a smart TV can support a variety of input devices, including smartphone-based remote-controls, such as Samsung's Peel-smart-remote-control[1], and brand-dependent smart remote-controls, such as LG's Magic-remote-control[2], Samsung's Smart-remote-control[3], Apple's TV-remote-control[4] (comes with Apple's STBs), etc. However, these remote controls provide limited facilitations to the aforementioned secondary activities. Therefore, we cannot expect the same interactions from viewers as they usually do with computers and smartphones [28,29]. Here, we present some scenarios as an example that highlights the limitations in existing systems:

Scenario 1. The exact identity of the viewer(s) is still challenging. Besides, the most recent watching activity on a smart TV cannot be associated with every member of a family or group. For example, a kid is watching YouTube's cartoons on a smart TV. These current watching activities are predicted and calculated by the recommender system of YouTube for further recommendations. However, after leaving the watching room by the kid, the next viewer(s) will receive a good amount of recommendations about cartoons on YouTube. It is because neither the service provider (recommender system) nor smart TV knows the exact identification about viewer(s) currently watching the content. For the exact identification of viewer(s), some systems [17,30,31] have achieved better recommendation results by detecting the faces in front of a smart TV. Such methods may lead to the privacy and security issues of viewers (see section 3 for more details).

Scenario 2. The recommendations based on the user's profile information is not viable due to the shared nature of a smart TV. For example, the activities for browsing, searching, and watching by different members of a family or group cannot be linked with one profile built by the recommender systems. For example, a smart TV viewer wants to access some services or install some apps from an app store. In this case, he/she has to register the smart TV/STB with an email address. Now, the recommender system will use this login information (age, gender, address, etc.) and will recommend items to that user. However, this registered smart TV/STB can be enjoyed by entire family members, and hence the recommendations will not be relevant to every family member. For group recommendations, numerous techniques have been proposed, such as aggregated predictions and aggregated models for preferences merging [32,33]. All such techniques are least effective in a smart TV watching scenario due to the viewer's diverse interests and privacy leakages (see section 3 for more details).

In a smart TV watching environment, we have to move from data-centric approaches (based on content profile) to user-centric approaches (based on end-user profile) because the recommender systems are developed for end-users, and thus the assessment and identification of end-user should be given more weight [34,35]. This paper suggests that the focus should be on the viewer(s) in front of a smart TV along with other parameters, such as history, profile, etc. Moreover, for tailoring more relevant and precise recommendations for smart TV viewer(s), the existing recommender systems and algorithms need to adapt itself to the varying watching behavior and should consider the dynamic interests of watching group(s) in front of a smart TV. The contributions of this paper are:

- A detailed yet comprehensive discussion on the existing recommender systems, approaches, and algorithms in the context of a smart TV.
- It highlights the issues and challenges that affect the recommendation results to an individual or group of viewers, specifically in smart TV watching scenarios.
- It presents some research opportunities to cope with the issues of recommendations on a smart TV.
- A subjective study for validating the factors (discussed in section 3) that could affect the recommendation results.
- In last, the results and analysis of subjective study are discussed in detail.

The paper concludes that the existing recommender systems and algorithms need further investigation for treating the smart TV a different device from other connected devices, such as computers and smartphones. The reason is that it does not consider the watching behaviour and exact identification of group members in front of a smart TV. The recommender systems, approaches, and algorithms need to be thoroughly investigated for a smart TV watching environment. Enhancing such results may contribute to e-commerce, e-business, and user satisfaction. The rest of the paper is organized as follows. Section 2 is Related Work on recommender systems in the context of smart TV and connected TV. Section 3 is a discussion on Factors that affect the recommendation results on a smart TV. Section 4 is the Methods and Material. Section 5 is related to Results and Analysis. Section 6 is

[1] https://www.samsung.com/za/support/mobile-devices/what-is-the-peel-smart-remote-application/

[2] https://www.lg.com/us/remotes

[3] https://www.samsung.com/global/tv/blog/evolution-of-the-smart-remote-control/

[4] https://support.apple.com/en-us/HT205305

Research Opportunities that may help in extending this research work in the field of personalized and group recommendations for smart TV viewer(s). Section 7 Concludes the paper. References are enlisted at the end.

2. Related work

The consumption of the Web content in a lean-back mode with little efforts brought the idea of smart TV [36,37]. Till now, millions of households have shifted from legacy TV systems into smart TVs [38]. As per a report by Research-and-Market [39], a unit shipment of smart TV is expected to raise about 193.7 million (in 2017) to 249.9 million (in 2023) with 4.3% compound annual growth rate. The smart TV provides infotainment to all age groups, and that is why the average time spent (in hours) in front of a TV is far exceeding the combined activities on smartphones and computers [40].On the other hand, the Web is growing at full pace, and a huge collection, including made-for-TV-movies, videos, clips, online web-based live channels, etc., are available for watching on a smart TV. Because of this, browsing and searching for relevant items on the web is time-consuming and a cumbersome job [15]. Besides browsing and searching, recommender systems help in coping with the problem of information overload [18]. The watching behaviour and time sepnt infront of smart TV may vary due to regional, cultural, and social values. In a study [26] the daily time spent on watching smart TV is up to 8 h per day.

Table 1 shows some most popular smart TV hardware and software technologies.

Moreover, the watching time fluctuates due to mood, different events, vacations, etc. The most dominant watching activities on smart TV are videos, live channels, movies, and clips. A most important factor of watching smart TV is that it is enjoyed in groups [26]. It worth mentioning here that the formation of group and detecting exact group member is not only challenging but also requires extra resources such as camera and mic [37].

The recommender systems infer user interests by utilizing various sources of data, such as clicks, navigation, demographics, feedbacks, tec., [41,42]. The user's activities, i.e., clickstreams, key presses, etc., are logged on the service provider's server that may provide signals to the recommender systems [20]. Besides, the user profile information is used as input for recommender systems; however, in most cases, the smart TV is used as a shared device, and hence calculating profile-based user's preferences are difficult to predict. Some smart TV brands have embedded intelligent systems for enhancing recommendation results on smart TVs. For example, Samsung has introduced the *S-recommendations*[5] feature with some smart TVs, in which the contents are delivered based on the user's interests. Similarly, LG's smart TV has the *On-Now-Search & Recommendation*[6] feature, which recommends items from all available sources based on watching history and popular shows. The recommender systems recommend items based on the user preferences that are built from data that comes from the client-side, i.e., user side. Fig. 1 shows a general view of the recommendation process on a smart TV. Different objects can be recommended to smart TV viewers, such as advertisements (ads), stored videos, videos on demand, live channels, dramas, apps, shows, etc.

In a typical smart TV watching environment, we have two types of watching scenarios, i.e., single-user watching scenario and group watching scenario. In a single-user scenario, the recommendations are tailored for single-user called personalized recommendations, which is one of the most prominent applications of recommender systems [43]. For example, books are normally recommended based on single-user interests [44]. From literature, it is confirmed that the recommendations to a single-user maximize the satisfaction [45] and relatively an easy task due to the reason that a single-user profile can be built from that particular user's feedbacks, profile information, etc. In a group watching scenario, the contents are delivered to a virtual group profile, which is based on two or more profiles. The applications of group recommendations include recommendations of movies, news, dramas, sports events, etc., [46]. Therefore, group recommendations are also important factors that need to be considered [32]. The group members may have different interests, ages, gender, and numbers. In a smart TV environment, a single viewer can be recognized by using different sensors, such as a camera or microphone. The camera can be used for face and gesture recognition, whereas a microphone can be used for voice recognition. However, such recognition systems for generating group are not only challenging but also the chances of irrelevant recommendation results are highly probable. In subsequent paragraphs, we discussed the most popular systems and relevant research in the context of recommendations on smart TV.

The accurate identification of a viewer may play a key role in personalized recommendations. In this connection, the popular streaming services that provide interactivity and recommendation services to a connected TV is Hybrid Broadcast Broadband Television (HbbTV[7]). The HbbTV has created Personal Recommendation Engine Framework (PREF) at the back-end that works on the philosophy of content-based filtering techniques, i.e., Users' rating, preferences, items, groups, characteristics, etc.,[17]. The HbbTV services have been criticized in the literature for exposing the viewer's privacy [47]. Moreover, hackers can gain full control of HbbTV by launching over-the-air attacks [10]. In such a case, the personalized recommendation may compromise the security and privacy of smart TV viewer(s).

MovieLens[8] is a web-based movie recommender system. It invites users to rate any movie on their site and get a personalized recommendation for other similar movies. On the bases of the viewer's rating, they performed predictions and personalized recommendations. In the case of a smart TV, such types of web-applications are least effective to recommend relevant items because rating and tagging are among difficult activities to perform by using a remote control. Similarly, PolyLens [48], is a web-based movie recommender system that uses collaborative filtering techniques to recommend items to group users rather than individuals. The issue with MovieLens and PloyLens systems is that both are reliant on collaborative filtering techniques, which is difficult and sometimes impractical in a smart TV environment. Kim and Lee [49], worked on a group recommender system that was focusing on home-group viewers in the television domain. They used various approaches for making a model of a group from a real-world dataset. The results of the study show that the recommendation system based on Consensus Function Approach, Maximum (most pleasure strategy), and the Average strategy is more suitable than Minimum (Least Misery Strategy) for homegroup viewers [49]. Still, the generation and identification of a group member are still challenging. Barragáns-Martínez, et al. [50] and Martínez, et al. [51] proposed a hybrid approach (content filtering and collaborative filtering) to recommend TV programs. For this purpose, they developed *queveo.tv*[9], which is a web 2.0 TV program recommender system. Besides the hybrid approach, the system supports all features of social networking, such as communication among users, tagging content, rating, and comments, etc. As discussed, socialization is a rare activity on a smart TV, which makes such approaches least effective [26].

TV-Predictor [52] is a personalized program recommender system developed for smart TVs. They used an automatic tracking of the viewer's watching behavior and then recommend items. But in-depth

[5] https://www.hardwarezone.com.sg/tech-news-samsung-introduces-revamped-smart-hub-and-s-recommendation-voice-interaction-feature-2013-

[6] https://www.lg.com/us/support/product-help/CT10000018-1405575967481-other-premium-applications

[7] https://www.hbbtv.org/

[8] https://movielens.org/

[9] http://queveo.tv/

Table 1
Most Popular Smart TV hardware and software.

Operating System	Type of Operating System (OS)	Channels Customization Support	IDE for development	Based on	Updated	External Hardware Support
Google's Android	Open Source	✓	Android Studio	Linux OS	✓	✓
Apple's tvOS	Proprietary	✓	Xcode	Unix-like, BSD	✓	✓
Samsung's Tizen	Open-Source	✓	Visual Studio/Tizen Studio	Linux Kernel	✓	✓
LG's WebOS	Open-Source	✓	WebOS SDK	Linux OS	✓	×
Microsoft's Windows	Proprietary	✓	Visual-Studio	Windows OS	✓	✓

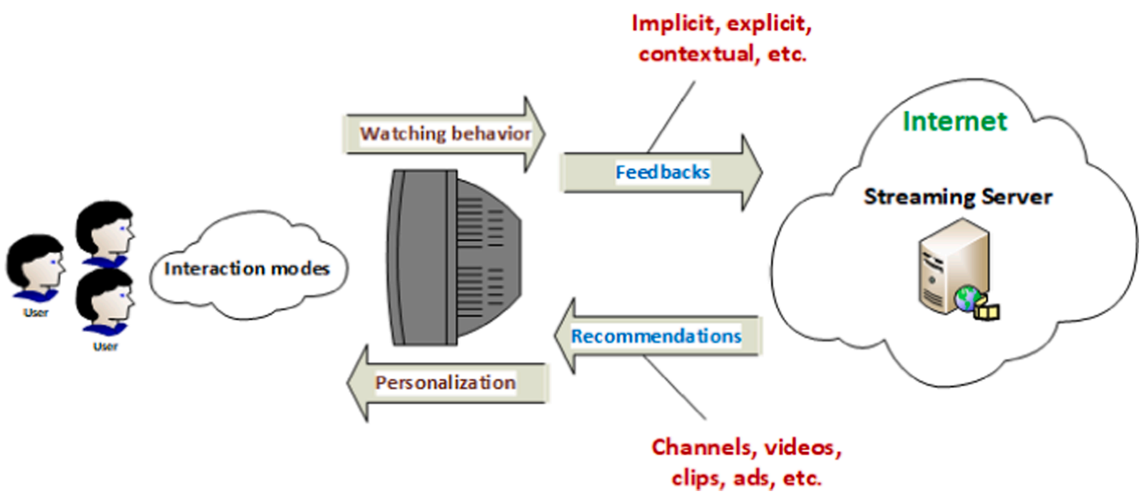


Fig. 1. General overview of the recommendation process on smart TV.

analytics of the viewer's data may lead to privacy issues. OntoTV [53] is developed for the management of different sources of TV-related content. It uses semantic multimedia techniques with the help of ontologies for different TV-related content. Similarly, Kim, et al. [54] proposed searching and recommendation methods for TV programs, which are based on the contents and viewers ontologies. They have designed the ontology model of TV programs for defining the semantic structure of the content. The work was extended by Kim, et al. [55] and presented a TV program recommendation approach based on the construction of the TV program domain ontologies. They proposed a similarity matching technique and recommend a method for TV program recommendations for mitigating the issue of information overload. A cloud-based program recommender system (CPRS) is proposed [56], which is used to improve the channels recommendation system by the formation of groups that have similar tastes. In CPRS, the user profiles are clustered and then grouped by the K-means clustering algorithm. However, in smart TV watching scenarios, the formation of groups that have similar taste is not an easy task because of a diverse set of users and interests.

Kurapati, et al. [57], proposed a multi-agent TV recommender system that considers three types of user information, i.e., history, preferences, and feedback, and then generated recommendations for a viewer. However, smart TV is not a single user device, in which the history, preferences, and feedback cannot be associated with every member of a family or group. Chang, et al. [58] proposed a TV program recommender framework, which integrates the Web 2.0 features into television sets and smart TVs (set-top-boxes). The authors claimed that the user's preferences might be influenced by their friends, family, colleagues, etc. Therefore, it is reasonable to take a user's social metadata into account for enhancing recommendation results. The social metadata, such as comments, ratings, etc., is not necessarily available for every viewer of a smart TV. Li, et al. [20] developed a two-stage framework for building a TV recommender system. First, the proposed framework automatically learns the number of viewers in a watching group, and then the Mixture Probabilistic Matrix Factorization (mPMF) model is proposed for learning the mixture preference of a television program. Similarly, Yu, et al. [59] proposed a TV program recommendation for multiple viewers based on merging user profiles; But the actual identity of the group members is still challenging. RecTime [60], proposes a real-time recommender system for online broadcasting, which consider time factors and user's preferences simultaneously. They developed a new recommendation algorithm, which captures the user's status as well as the status of the broadcasting shows. Similarly, Engelbert, et al. [61], presents an approach for a user supporting personal video recorder. They implemented a Bayesian classifier-based recommendation system. The system analyzes a user's watching behavior for recommending content. However, watching behaviour cannot be linked with every person in a group or family. Smyth and Cotter [62], the authors describe the development of Personalized Television (PTV[10]) listing system, which handles the information overload by providing an Internet-based personalized listings service. Yu, et al. [16], has developed a personalized EPG based on user switching channel behavior on the connected TV (IPTV) to enhance the searching process. The system recommends the channels based on the already watched channel's information. The threshold value was about 10 min for this recommender system. However, such types of recommendations are effective only in personalized and for a single user profile. Ardissono, et al. [21], the authors proposed a model in which the recommendation techniques are applied in the Personal Program Guide (PPG). Both Electronic Program Guides (EPGs) and Personalized Program Guides (PPGs) assist a user in selecting a program of interests; yet, the user feels overwhelming by the provision of many program options [56]. The modern smart TVs are equipped with

[10] http://www.ptv.ie

Table 2
Existing Work on Recommender System for TV Related Contents.

Study/System	Personalization	Group Recommendation	Socializing
RecTime [60]	Yes	–	No
TV-Predictor [52]	Yes	No	No
OntoTV [53]	Yes	–	–
CPRS [56]	Yes	–	No
HbbTV [47]	Yes	–	
Queveo-TV[a]	–	–	Yes
AIMED [80]	–	–	–
YouTube[b]	Yes	–	No
Personalized Program Guide [21]	Yes	–	–
PolyLens [48]	–	Yes	–
MovieLens[c]	–	–	Yes
Netflix[d]	Yes	Yes	Yes
GroupLens[e]	–	Yes	Yes

[a] http://queveo.tv/
[b] https://www.youtube.com/
[c] https://movielens.org/
[d] https://www.netflix.com/pk/
[e] https://grouplens.org/

an Automatic Content Recognition system that recognizes the currently watching contents by a smart TV viewer(s) [63]. It may help in personalized content recommendations; however, due to frequent switching of viewers in front of a smart TV makes it difficult to recommend relevant items, especially for a group of viewers.

Content clustering techniques play an important role in the process of recommendations. The TV-related content can be clustered to enhance not only the recommendation results but also searching results. Zhiwen, et al. [64], proposed a fuzzy clustering technique to classify TV programs on the broadcaster side. By using this technique, the group recommendations are possible to recommend the related content to users. Xu, et al. [65] presented an exploratory study about grouping the users on their behavior by using the clustering techniques. They presented a user modeling approach to minimize the effects of the cold-start issue. Xu, et al. [66] further extended the above work and presented a Catchup-TV recommendation by using the approaches for recommending new contents-based on watching history. However, watching history on a smart TV is not the true representative of the whole group. Yang, et al. [67], presented the Personalized Channel Real-time Recommendation System (PCRS) framework, which works in an IPTV system by using deep learning and users channel switching sequence. It works by channels switching history only and does not consider the profile information.

The context also plays an important role in context-aware recommendations [68,69]. Villegas and Müller [70] categorize the context into five general categories, i.e., Individual, Location, Time, Activity, and Relation. These contexts provide an important input to recommender systems; however, in the context of smart TV watching scenarios, these contexts (except location) are difficult to predict. These systems are well-suited for a single user (single profile). As discussed, in a smart TV watching scenario, multiple profiles pose a challenge for delivering personalized recommendations [71]. Moreover, there may be frequent switching of group members in front of a smart TV. Such types of video-sharing websites cannot handle these types of issues due to the reason that information about group members are normally based on estimates and predictions [72,73]. Recommender systems use a variety of algorithms and approaches (see Table 2) for making recommendations relevant and precise.

Summarizing the existing literature, we can conclude that the actual identification of the user/group-member in a secure way is of utmost necessity for the delivery of personalization services, including better-personalized recommendations. The user feedback in the form of implicit and explicit may further enhance the recommendation results; however, explicit feedbacks are difficult due to the lean-back nature of a smart TV. Similarly, implicit feedbacks are not simple to calculate because smart TV is enjoyed in groups. Incorporating the social metadata with recommender systems have proven improvement; though the social networking sites on a smart TV are rarely used, because, the smart TV is normally not limited to a single person. The group recommendation is an essential factor for smart TV viewers; however, predicting the actual group members and satisfying each member of a group is still challenging. There may be frequent switching of the user in front of a smart TV, which makes it difficult for personalized recommendations. The better user/group modeling for securely identifying group members may enhance the personalized group recommendations on a smart TV. Section 3 discusses the factors that could affect the recommendation results on a smart TV

3. Factors influencing the recommendation process on smart TV

In this section, we discussed some factors that influence the recommendation process on the smart TV. The factors are discussed in the perspectives of watching behaviour, the distinct nature and purpose of smart TV, and the techniques used by the recommender systems.

3.1. Smart TV is a group device

The group recommendations play a vital role in a smart TV watching scenario. The reason is that in most of the households, the smart TV is enjoyed by the whole family in the group [44]. The family members

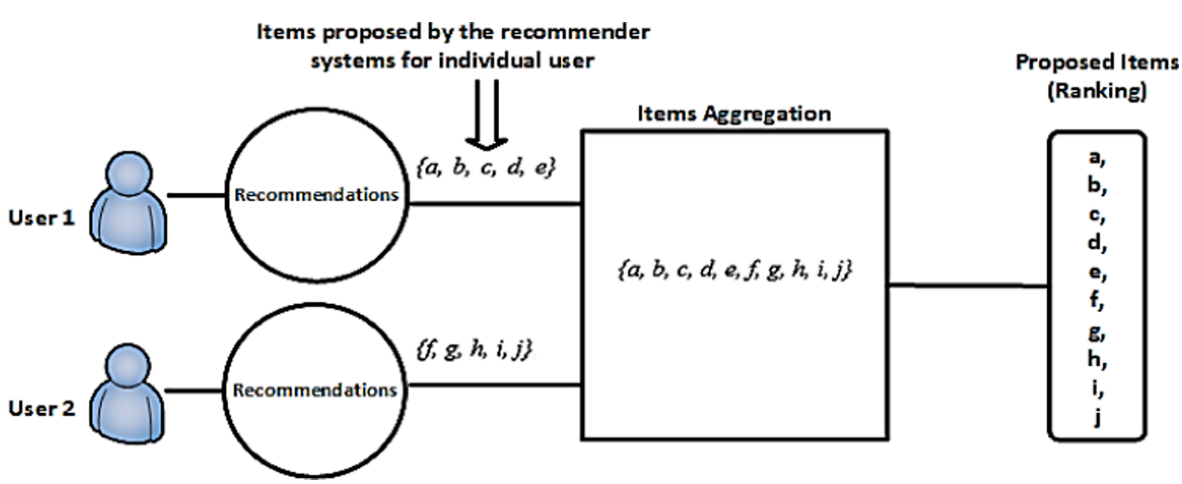


Fig. 2. Aggregated prediction techniques.

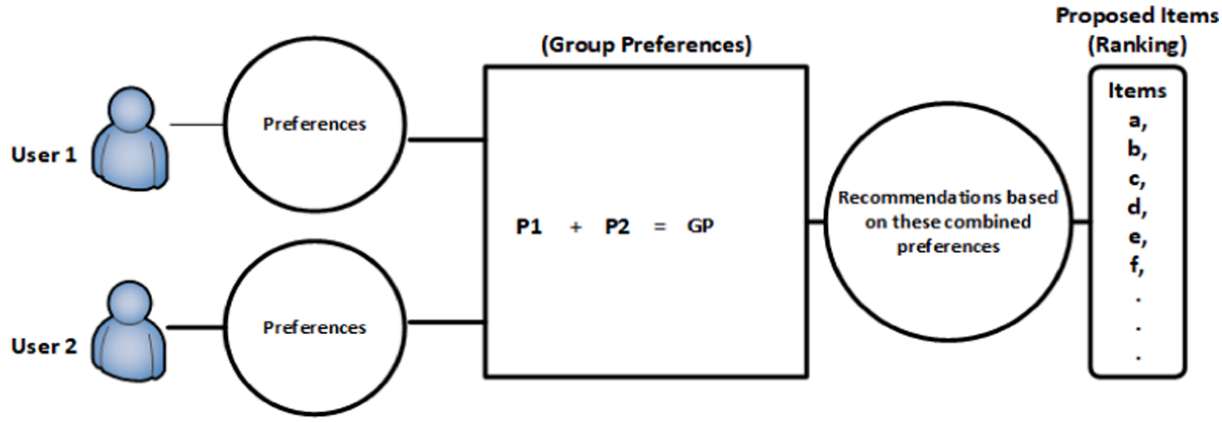


Fig. 3. An Aggregated model for preferences merging.

formed different groups that may consist of different numbers, tastes, ages, and gender. The member of a group can leave and re-join the TV watching room anytime, and hence predicting, maintaining, and updating multiple profiles on a smart TV is not an easy task. Besides, the logging information plays a vital role in personalized recommendations. However, a smart-TV logged-in by a single email address can be enjoyed by the entire group or family members (discussed as scenario 1 in the introduction section). Moreover, there may be many viewers, having diverse interests and preferences behind a single TV that make it difficult to predict the accurate preferences of a closed group or the whole family [20]. The two widely used approaches by the group recommender systems are (a) aggregated predictions and (b) aggregated models for preferences merging of individuals in a group [74–76]. These methods for the identification of group members are based on estimations and predictions. Besides, due to privacy issues and diverse interests of users, the preferences merging and aggregate predictions are not feasible approaches [45]. In sub-sections, we have discussed in detail the most widely adopted strategies for group recommendations.

3.2. Aggregated predictions

In this approach, the recommended items for different users are first aggregated. A list of these aggregated items is then ranked according to the preferences of users. An item is then recommended from this list, as shown in Fig. 2. Besides some good results, this approach is not feasible in a smart TV watching scenario because each user has a diverse taste, and hence the recommended items may become irrelevant for most of the group members. For example, if we have distinct items of different users, such as *USER1= {a, b, c, d, e}*, and *USER2= {f, g, h, i, j}* where *a, b, c, d, e, f, g, h, i, j* are initially recommended items. Merging the list by using aggregated prediction techniques may generate a list *{a, b, c, d, e, f, g, h, i, j}*. Now, the recommendation items based on this list may be irrelevant for *USER1* as well as for *USER2*. Therefore, the recommendations based on items aggregation may not satisfy every user in a group.

3.3. Aggregated model for preferences merging

In this approach, the user profiles are merged for making a virtual group profile, as shown in Fig. 3. The items are then recommended to this group-profile instead of individual profiles. This approach is widely used for group recommendation. However, in a smart TV environment, the profile merging strategies are not viable and may lead to privacy issues.

For example, if a *USER1* has preferences P1 and *USER2* has preferences P2, then GP represents the Group Preferences of a group profile. Now, the recommendations on the bases of such techniques may generate irrelevant recommendations for every individual in a group because of variable interests. Therefore, the exact identity of every member and satisfying every group member is still challenging.

3.4. Limitations of recommendation approaches

The recommender system uses different approaches, such as content-based, collaborative filtering, and hybrid approaches [22]. It takes the feedback from the client side as input for recommendations; however, user feedback is exceptionally different in a smart TV environment. In the below subsections, we discuss the issues and challenges of the recommender systems from server perspectives. Fig. 4 shows some common recommender system approaches.

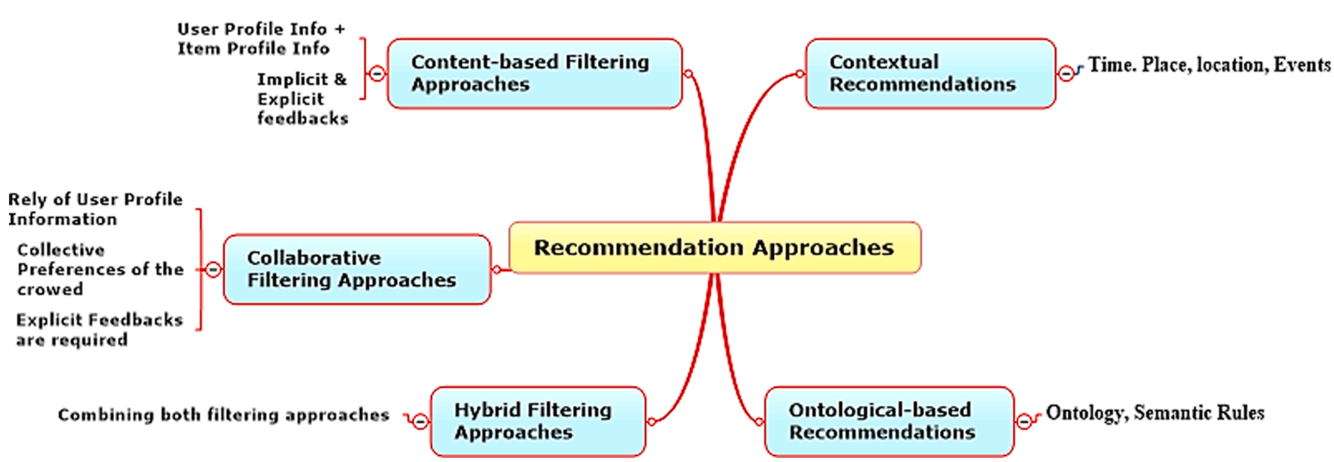


Fig. 4. Existing Recommendation Approaches.

3.4.1. Collaborative filtering

The collaborative filtering approach is a recommendation technique which uses the collective preferences of different users and recommends items to a user having similar taste in the circle. It relies on user feedback and gives signals to recommender systems as input. The feedback may be explicit, implicit, or a combination of both [77]. Explicit feedbacks required explicit actions, such as rating, likes/dislikes, etc., from a user, whereas implicit feedbacks are generated by the recommender system from user activities, such as navigation, clicks, etc., [78]. Explicit feedbacks on a smart TV is a difficult task because of limited facilities provided by the legacy remote-control. Similarly, secondary activities, such as commenting, liking/disliking, etc., on the remote control, is a cumbersome job [55]. Therefore, in the case of smart TV watching scenarios, implicit feedbacks may work better than explicit feedbacks [17,79]. Generally talking about collaborative filtering techniques, we argue that it does not yield better results for smart TV viewers. It is because we cannot expect extensive interactions from the user while watching content on a smart TV. Moreover, collaborative filtering techniques depend upon other viewer's data, without which we cannot expect good recommendations [80]. Collaborative filtering techniques have some issues, such as the cold-start problem, grey-sheep problem, data sparsity, scalability problem, and the synonym problem [4,81]. To overcome the issue of the cold-start problem up to some extent in the smart TV watching scenario, the non-personalized algorithm, called *Top-N*, recommends the top-most relevant content to a viewer [82]. The collaborative filtering techniques use different algorithms, such as Cosine Similarity, Pearson-R Correlation, Slope one, Singular Value Decomposition (SVD) [83].

3.4.2. Content-Based filtering

In this technique, the recommender systems build a user profile; after which, the recommender system compares program attributes (item description) to a user profile and generates similarities between them [80]. Based on these similarities, the suitable items are then recommended to a user. It uses different parameters, such as watching history, comments, likes/dislikes, and description with an item(s). When the description of an item matched with a user profile information, history, etc., then that item is recommended to a user [84]. The content-based filtering approach suffers from over-specialization [80], which means that when we have a large set of items, then it is difficult to match the user's profile information with items description. Normally, the content-based filtering algorithms considered smart TV as a personalized device, such as a personal computer or smartphone. Normally, a smart TV is enjoyed by an entire family or closed group [85]. In this case, the smart TV profile (single profile) may not be the true representative of the entire group/family [20,86]. Some work has been done [87] on combining time factors with watching history. However, in the context of a smart TV, predicting the exact number of viewers, their ages, and gender information from watching history has not yet achieved. The smart TV is not the true representative of all users [86].

3.4.3. Hybrid filtering approaches

The hybrid recommendation techniques combine both approaches to get better recommendations [88]. In a smart TV watching scenario, combining both content-based filtering and collaborative filtering techniques may not yield better results; because of the inherited issues of both. The collaborative filtering techniques failed due to the lean-back nature of smart TV, whereas content-based filtering techniques failed due to single profile representation.

3.4.4. Contextual recommendations

To add some meaningful context, such as time, location, events, etc., with recommendation techniques are called a contextual recommendation [89]. The existing recommender systems are not considering a rich set of available contexts [90], including both personal contexts as well as environment contexts. It is argued that rich collection of contextual information, such as location, events, hours of the day, days of the week, weeks of the month, months of the year, time factor, age factor, gender info, etc., can be integrated with a recommender system that may further enhance the personalization services including recommendations to a viewer or group of viewers. For example, if on a working day, all the family members are available at home indicates a "local holiday/vacation" context. Similarly, the availability of most family members at night-time indicates a context for group recommender systems. Some work in [91–94] has already been done on context-aware recommendations for TV-related content; however, the combination of rich contexts may further improve the recommendation results on a smart TV.

3.4.5. Ontological-Based approaches

Ontologies have been widely used for enhancing recommendation results [95]. The ontological approaches for content retrieval and recommendations of TV-related content have been done in studies [96,97], and proved the importance of ontologies for better recommendations. However, in a smart TV case, the recommendations can be further enhanced by supplying better signals from the user-side, i.e., smart TV. The ontological-based techniques, in which we used ontologies or semantic rules for recommending objects of interest [83].

3.5. User/Group modeling approaches on smart TV

The smart TV is commonly used for streaming web-based content, including live channels, videos, audios, and other related contents [98]. Most of the recommender systems focus on personalized recommendations. Therefore, all the activities of a user are tracked and logged for the better-personalized recommendation [81]. It also tracks the information, such as user searching behavior, watching history, keywords supplied, demographics, login information, locations, Media Access Control (MAC) address, IP address of a device, etc. This information is sufficient for personalized recommendations and well-suited for computer and smartphone users. It may fail to predict the viewers' preferences on smart TVs. There are some vulnerable features of a profile that may cause security and privacy issues. Table 3 shows the profile components and their effects on privacy and security in the context of smart TV watching scenarios.

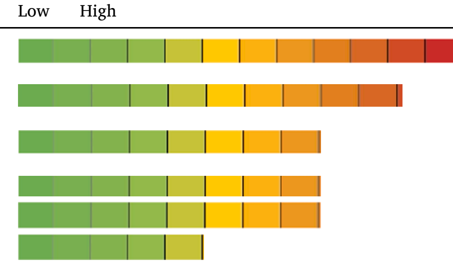
In sub-sections, we discussed the issues of recommendations from the smart TV (client-side) point of view.

3.5.1. Watching behaviour

The watching behavior on a smart TV is significantly different from other devices, such as computers and smartphones. Despite the emergence of new gadgets to spent leisure time on the internet, TV watching remains the most popular activity around the globe [38]. Similarly, smart TV is the most liked medium for watching the entertainment-related web-based content, including videos, games, music, etc.,[99]. This watching behavior is resembling legacy TV systems, which is less

Table 3
Profile components and their effects on privacy and security in the context of smart TV.

Profile Components	Security and Privacy effects (Low → High)
Biometric (Face, fingerprints, etc.)	
Logging data (email etc.)	
Clicks/Presses (navigation)	
Location	
IP Address	
Demographics (Age, gender, etc.)	



interactive and enjoyed in passive mode. Therefore, we argue that the expected feedbacks from a user watching a computer or smartphone cannot be treated in the same manner with the feedbacks come from smart TV viewers. Moreover, relying on pull approaches in the context of smart TVs may not always generate relevant recommendations. Hence, the recommender systems should adopt the push mechanism for recommending related items.

3.5.2. Multi-user device

The prediction, maintenance, and updating of multiple profiles on a smart TV is not an easy task because it is mostly enjoyed in groups as a shared device. A variety of techniques have been used for personalized recommendations, such as profile generation, profile merging techniques, face detection, and recognition systems, data mining techniques, etc. However, such methods may lead to privacy and security issues [10]. We argue that the viewer's privacy should not be compromised. It is because leaking such data, i.e., watching behavior, may lead to serious privacy threats. Different sensors may be used for the identification of viewers in front of a smart TV, such as a camera for face detection & recognition, microphones for voice detection & recognition, etc., [100–102]. Such identification may further increase the risk of privacy leakages. Moreover, approaches such as clickstream analysis, data mining techniques, and in-depth identification of a viewer may lead to security and privacy threats[17]. The manufacturers usually ignore the security and privacy issues related to smart TVs; though it is an essential concern for most smart TV viewers [10].

3.5.3. Unpredictable social metadata

Social metadata plays a vital role in generating relevant recommendations[103]. Some recommender systems, such as discussed in [57,103,104], use the social metadata for improving the recommendation results. Socializing on a smart TV is a rare activity. Despite the interactive nature of the smart TVs and usefulness of social data, the user-driven activities of web 2.0, such as commenting, blogging, likes/dislikes, etc., are unusual activities on smart TV [20]. That is why the main activities on smart TV are limited to watching movies and videos on the big screen [105,106]. Some well-known video sharing websites, such as YouTube[107], Netflix[11], Hulu,[12] use social data for recommendations. However, enjoying such video-sharing-websites on smart TV provides limited opportunities to perform activities like tagging, commenting, liking/disliking, etc., and hence the recommender systems which rely on such data may not generate accurate results.

3.5.4. Passive interaction

The user interaction with a connected device enriches a user profile, which in turn provides information to recommender systems for recommending relevant items [108,109]. The complex nature of the interaction with the device may limit the frequent interactions. Most of the existing smart TV UIs are overloaded by providing more features and options. This phenomenon is called bloating up the smart TV [110]. The smart TVs, including STBs, have full support for wireless keyboards and mouse that makes interaction an easy task; however, most of the viewers use the remote control as a primary device for communication [8]. Therefore, the recommender systems relying on user interaction are not well suited for a smart TV environment.

3.5.5. App-based channels

The channels of a smart TV are the apps that stream content from channel streaming servers [111] or video sharing websites. The recommended items are displayed on the home screen of the smart TV, which is refreshed based on user activities. A common approach for recommendations on a smart TV is the recommendation of items within a specific app that is currently running. For example, Netflix movies are recommended within the Netflix app. Outside this app, the recommender system of Netflix cannot recommend items from other sources. Netflix and YouTube have different algorithms for recommendations [112]. The viewers can customize a smart TV home-screen and channels (apps) [113], but scrolling a long list of channels is not feasible for smart TV viewers.

[11] https://help.netflix.com/en/node/100639

[12] https://www.hulu.com

4. Methods and Material

A random sample of 23 families having a smart TV (connected TV) was selected for analysing the most significant factors that could affect the personalized recommendations. Before the survey, the consent and purpose of the study were discussed. A total of 69 participants were selected from these 23 families and were requested to share their watching experiences of the last one month. A mixed-method survey was conducted using closed-ended questionnaires and interviews. Table 4 shows the detail of the selected sample.

4.1. Survey contents

We used a mixed-mode survey in which we asked several questions for finding the six factors that are either directly or indirectly interrupt the recommendation process, specifically in the context of a smart TV watching environment. The six factors were extracted and discussed in the results and analysis section. In the questionnaire as well as in the interview, we asked about the number of smart TVs in their home as well as about the watching of smart TV in either group or individually. By this factor, we want to confirm that the recommendation on smart TV should consider all members of a group. Then we asked about switching and navigation between channels (apps) and other contents. By this factor, we want to elicit viewer the complex interaction between smart TV and user, which affects the profile enrichment and, in turn, affects the recommendation results. Similarly, we asked about the interaction level. This factor will show that frequent interaction certainly enriches the user profile, but the user wants less frequent communication. Moreover, we asked about the frequent switching of users in front of smart TV. The smart TV cannot handle the frequent switching of users, and hence recommendations based on user history or recent activities can be related to every member of a family. We asked about the use of social networking sites on the smart TV. This factor is investigated to show the importance of social metadata for improving the recommendation results. Furthermore, we investigated the watching behaviour on smart TV, i.e., the basic and most prominent watching activity on a smart TV. This factor will confirm whether the smart TV is a distinct connected device from other connected devices or not. In last, we investigated the time spent in front of smart TV. This factor will show the importance of enhancing the recommendation specifically for smart TV users.

5. Results and analysis

The gathered data were analyzed based on different parameters and factors, as discussed. The sub-section discusses each parameter in detail. These parameters are discussed only in the context of smart TV.

Table 4
Demographics.

Participants	Demographics	Total Participants	Percentage	SD
Age Group	10–20	16	23.18	3.03108
	21–30	13	18.84	
	31–40	19	27.53	
	> 41	21	30.43	
Gender	Male	41	59.42	6.5
	Female	28	40.57	

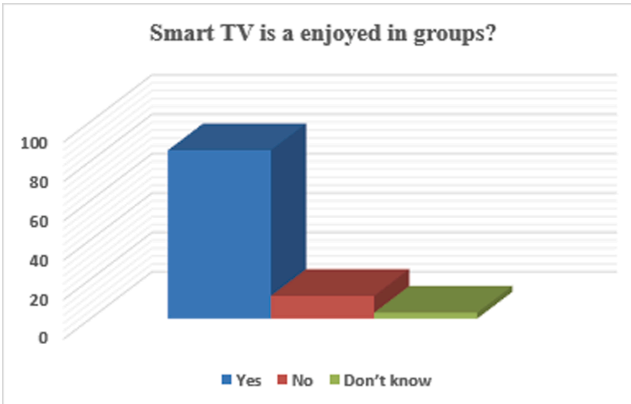


Fig. 5. Smart TV is a group watching device.

5.1. *Smart TV is a group device*

The watching behavior is significantly different from region to region. In this specific region, i.e., where the survey was conducted, most of the people watch TV in groups. From the collected responses, we analyzed that 85% of people watch TV in groups, as shown in Fig. 5. One major reason is that in 99% of households, they have only one TV for watching. We also found that in the night-time, most of the family members join the groups. It shows the importance of group recommendations, specifically on the smart TV. Furthermore, it shows that content recommendation on smart TV does not belong to a single user, i.e., personalization.

5.2. *Frequent switching of users*

An interesting statistic has been observed from the collected data. We asked about the switching of viewers, which is random every time with no proper sequence. From their response, 100% of random switching is observed, which shows that content recommendations based on history/preferences cannot generate accurate results on a smart TV. The results generated may be of no interest to every member of a group. Moreover, the maintenance of multiple profiles with frequent switching behaviour cannot be handled by the smart TV.

5.3. *Complex nature of interaction*

The more interaction with a device may enhance the profile, which in turn may enhance the recommendation results. However, the complex nature of the user interface of the smart TV may restrict frequent and smooth interaction. About 67% of participants talked about the complex interface of a smart TV, as shown in Fig. 6. They considered the searching, typing, tagging, and commenting are difficult activities by using the remote control, which shows that the enrichment of user-profiles by using clicks and press may have limited effects in the context of smart TV.

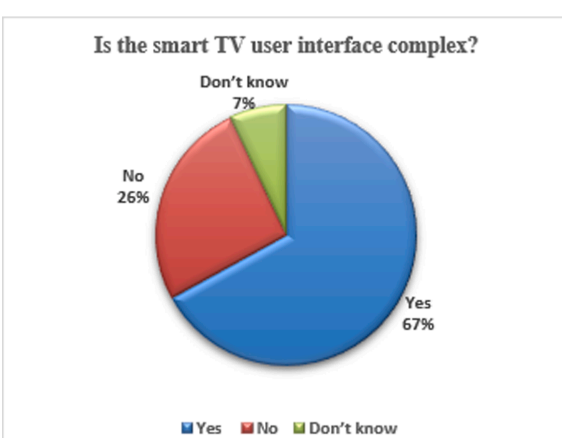


Fig. 6. Smart TV complex User interface.

Moreover, the channel switching difficulty level was surveyed by using a ten-rating scale. In the rating-scale, 1 was used for low difficulty, whereas 10 for more difficult. Comparing with the average difficulties score *(8.21)* of channel switching on smart TV with the average difficulties score *(4.36)* of channel switching on traditional TV shows that smart TV provides a more difficult interaction system than traditional TV. Similarly, an analysis of variances were calculated for confirmation as shown:

ANOVA: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
Smart TV	69	567	8.217391	2.054987		
Tradition TV	69	301	4.362319	2.910912		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	512.7246	1	512.7246	206.4982	4.64E-29	3.910747
Within Groups	337.6812	136	2.48295			
Total	850.4058	137				

In the *ANOVA* test, the *F* value is greater than the *F critical* value, i.e., *F > F-Crit*. Hence, we can conclude that there is a difference between channel switching on smart TV and traditional TV. The difference and difficulties are because of the smart TV complex interface.

5.4. *Social networking sites of smart TV*

This use of social metadata enriches the recommendation results. However, about only 01% of users use social networking sites on the smart TV, as shown in Fig. 7. One reason is that smart TV is a shared device that has the possibility of privacy leakages. It shows that the supplement of social metadata on a smart TV is limited, which in turn may affect the recommendation results.

5.5. *Prominent watching activities*

We collected data about the most prominent activities on smart TV. Not surprisingly, 54% of participants use the smart TV for watching live channels, 35% of participants used smart TV for videos watching, movies, clips, etc. About 2% of people use a smart TV for reading the textual data, such as news, wikis, etc. It shows that smart TV is used for watching and enjoying multimedia content. This watching behaviour provides limited clues for recommender systems and may affect the recommendation results.

5.6. *Time spending in front of smart TV*

The overall time spent in front of smart TV is variable. An average, 6 + hours/household was recorded. It shows the importance of recommendations on a smart TV. Enhancing recommendations on smart TV may improve the conversion rate, which in turn contribute to e-commerce.

6. Research opportunities

The relevant and precise recommendations of items may not only

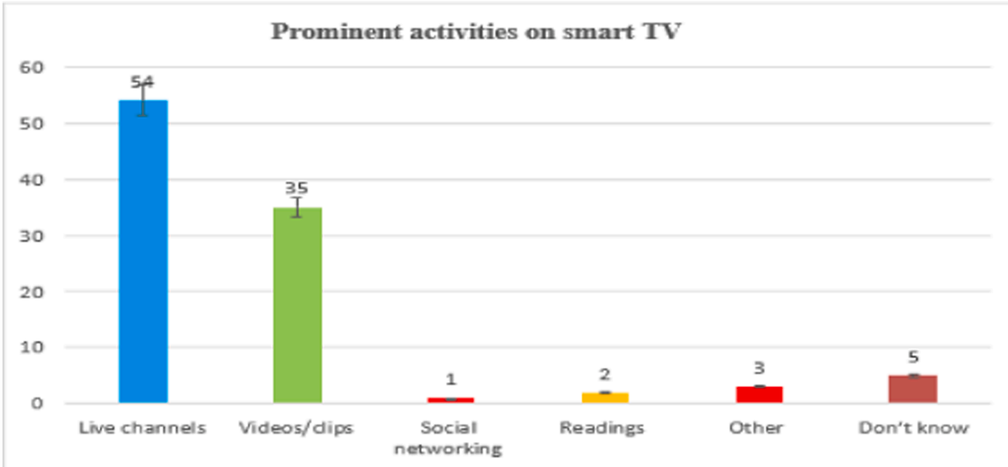


Fig. 7. Most prominent activities on smart TV.

contribute to the viewer's satisfaction but also may enhance the conversion rate. For example, Amazon and Netflix have reported 35% extra sales from their recommender systems [114]. The recommendations on smart TV should be given due attention to enhancing e-business and e-commerce. In the below sub-sections, we are presenting some research opportunities that may help the practitioners and experts of the field for redesigning the existing recommender systems according to the smart TV environment.

6.1. Enhanced User/Group modeling

The better user/group modeling techniques may improve the recommendation results. Most of the recent research work on the recommendation is trying to improve the signals in the form of implicit and explicit feedback; however, it ignores the user's actual presence, watching behavior, and the purpose of watching a smart TV. The identification of the viewer(s) should be in such a way that it may preserve the security and privacy of viewership data. As discussed, the exact identification of the viewer(s) may lead to security and privacy leakages [115]. Therefore, better usage of smart TV capabilities, such as camera, GPS for location detection, storage, and processing, etc., can generate more secure profiles. The existing recommender systems recommend items based on some context, such as the location of the device, time, keywords used, etc.; however, the lack of semantically enriched contextual information, such as regional events, age factor, gender information, local vacations, events related to some specific families/groups, etc., are not sufficiently considered by the existing recommender systems due to either the lack of availability or calculation of such information. We argue that seeking and incorporating such rich contextual information can further enhance the existing recommender systems for smart TV.

6.2. Emphasis should be on implicit feedbacks

In the case of personalized recommendations on a smart TV, the recommender system should rely mostly on implicit feedbacks [20]. As discussed, smart TVs are more interactive and can provide better clues for recommender systems. However, we cannot expect ratings, comments, likes/dislikes from a smart TV viewer. Therefore, the recommendation algorithms that consider the parameters mentioned above may not yield better results for smart TV viewer(s). We endorsed the argument in [20] that in a smart TV environment, the recommender system should rely more on implicit feedbacks instead of explicit feedback. In a smart TV watching environment, the recommender systems should concentrate on user-centric approaches (based on user preferences) because the users in front of a smart TV are more important than data, such as history, preferences, logs, etc. Besides predictions and estimation for preference calculation, the existing group recommendation techniques can further be improved by merging the preferences of the actual viewer in a group, especially for recommending items on a smart TV. By exploring ways and means for identification of an actual member of a group may enhance personalization services, including group recommendations. Moreover, the integration of social metadata may enhance the recommendation results [115]; however, social metadata belongs to a specific user. Therefore, such integration of social metadata should need more investigation for mitigating the issues of feedbacks from a smart TV perspective.

6.3. App-independent recommendations

Most of the recommendations appear on the home screen of a smart TV that is dependent on a specific channel (app). We argue that enhanced app-independent recommendation approaches can mitigate this issue of single-channel-monopoly by recommending items, i.e., games, video, clips, etc., from diverse data sources. In the existing practice, when you open a channel in a smart TV, that specific channel recommends the items. For example, in Android O[13] (Oreo) for smart TV, the channels are enlisted on the home screen in vertical format, and their recommended items are displayed against each channel in a horizontal format. Therefore, before opening a channel, very limited recommended items can be viewed on the home screen of a smart TV. Moreover, in the legacy TV system, opening, searching, and switching between channels was an easy task due to the limited number of channels. However, in a smart TV, the channels are now apps. Therefore, navigating between channels means navigating between apps, and that is a cumbersome job by using the traditional remote control [116]. The existing app (channel) should behave like a channel and should avoid so many presses/clicks for viewing the desired content. It is argued that better and adaptive user interfaces may mitigate such issues. We propose and recommend a universal user interface of the smart TV for enhancing usability, adaptability, recommendations, and learnability [29].

7. Conclusion and future work

This paper is an attempt to discuss the recommendation issues in the context of a smart TV, which is a lean back, non-personalized, and shared device. The existing literature on recommendations is focusing on personalization. It does not fully consider the diverse set of people (group), interests, ages, gender, and context. Similarly, the feedback and

[13] https://www.android.com/tv/

watching activities cannot be accurately interpreted by the recommender systems. To overcome the effects, numerous techniques have been proposed, such as face detection, in-depth analytics of user's data/log, location of the viewer, etc.; however, such techniques may lead to security and privacy of viewer(s). The watching behaviour on smart TV creates hurdles for personalized recommendations because the smart TV is enjoyed as lean-back device, mostly used for watching live videos and channels on the big screen. By summarizing the discussion, we argue that recommender systems should treat smart TV as a different device from other connected devices, such as computers and smartphones.

In contrast to data-centric approaches used by existing recommender systems, this paper suggests a user-centric approach for a typical smart TV watching environment. The findings of this paper suggest the design of a dedicated recommender system for smart TV viewers that have a better understanding of viewer(s) interest and have the least prone to security and privacy issues. In the future, we intend to extend this work for designing a group recommender system by exploring ways and means for user/group modeling that may enhance the personalization services on a smart TV. We aim to generate and maintain the anonymous and consolidated user/group profiles on a smart TV, which may help in extracting the interest of the exact viewer(s). Moreover, we aim to design a recommender system for smart TV viewers that will rely mostly on viewer's implicit feedback rather than explicit feedback. This paper may help the practitioners in designing a recommender system, including personalized group recommender systems, specifically for smart TV.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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