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Tailoring Recommendations to Groups of Viewers on Smart TV: A Real-Time Profile Generation Approach

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ABSTRACT The recommender systems predict and calculate user preferences for recommendations. However, such predictions and calculations are neither accurate nor viable in the context of smart TV due to the reasons that it is a lean-back, non-personalized device, and normally enjoyed in groups. Hence, group recommendations have utmost importance, specifically from the perspectives of watching smart TV. The existing group recommendation techniques predict the individual's preferences and then create a virtual group profile for recommendations. However, identifying and satisfying every group member is challenging. Numerous techniques have been proposed, such as face detection and recognition systems, but these systems lead to security and privacy issues. This paper proposes a smart TV-based recommender system that aims to identify the individuals and group members from their "age," "gender," and "number" information to overcome the biases that occur due to predictions and estimations of user's preferences. The study proposes a novel formula and age-gender matrix for generating anonymous, consolidated, and secure profiles, including group profiles on a smart TV. This study further proposes a novel method for finding a dominant character in a group by utilizing the user's ratings. Results show that the group decision has a significant impact on supplying social metadata, such as ratings, comments, etc., which in turn improve recommendation results. For materializing the proposed work, smart TV's processing, storage, and camera are utilized. The prototypical implementation has been tested and analyzed with improved recommendation results and viewer(s) satisfaction.

INDEX TERMS Recommender systems, smart TV, group modeling, personalized content.

I. INTRODUCTION

The rapid growth of web content makes it difficult to search and retrieve the content of interests and hence create the problem of cognitive and content overload [1]–[3]. To mitigate these issues, recommender systems play an important role [3]. The recommender systems are used to recommends related items to a user or group. In the context of smart TV, the content recommendation is the process of disseminating user-demanded TV content based on user preferences and context of use. It stores and deduced user's interests by using various data sources, such as context [4], user profiles, preferences, clicks, and feedback (rating, and likes/dislikes), etc., [1], [5]. However, a typical content recommendation algorithm delivers the programs to the end-users based on an individual's profile. It does not cater to the diversity comprising of family members and close groups. Thus, profile-based recommendations on smart TV needs further enrichment to recommend relevant content to these diversified groups. The user-centric approaches for evaluating the recommender systems are also used [6]. However, detecting the identity of a user or group from their watching activities is a difficult job, specifically in the context of smart TV. This paper is an attempt to tackle this issue by a novel user and group modeling techniques and recommend relevant items not only to individuals but also to exact groups in front of a smart in a secure way than available methods. For achieving this, we used off-the-shelf capabilities of a smart TV.

The idea behind the creation of a smart TV was to enjoy the web multimedia content in lean-back mode. It provides extended functionality in the provision of delivering digital content such as watching online dramas, movies, games,

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socialization, shows, video on demand, and virtual reality 360° contents [1]. However, the creation of this new generation TV, called smart TV, brings issues in the form of security, usability, recommendations, etc. The smart TVs are empowered with high processing capabilities, built-in support for sensors, gesture control, and facial and voice recognition, which enabled users to have better control over smart TV operations [7]. However, these capabilities increase the security and privacy risks [8], [9], and due to this, most of the viewers prefer to disable the camera and even microphone [10]. The camera of a smart TV has been used for the viewer's face detection and other personalized services, such as parental controls, personalized content delivery, etc., [11]–[15]. However, such systems may lead to severe privacy and security issues.

Moreover, the conventional approaches for content watching on smart TV are searching and browsing for the favorite content. However, browsing and searching for desired contents are difficult and time-consuming job. The searching process is even more difficult on connected and lean-back supported devices, such as smart TV. It is because the smart TV is usually enjoyed in passive mode and preferably less interactive. The television broadcasters have shifted their channels to the Web, which further increases the problem in searching and watching the relevant contents, especially the TV-related multimedia contents [16].

The focus of existing recommendation schemes on a smart TV is based on individual profiles, feedback, watching history, and location information. However, from smart TV perspectives, there may be groups of viewers having distinct ages, interests, tastes, etc., [3]. In such a case, the recommender system does not produce relevant recommendations. A significant amount of literature exists on group recommendations and can be used for recommendations on a smart TV. For example, the two widely used approaches by the group recommender systems are (a) aggregated models for preferences merging and (b) aggregated predictions [17]–[19]. However, both of these methods generate groups by estimating and predicting user preferences. In the aggregated predictions recommendation approach, the items are aggregated, ranked, and then recommended to a virtual group profile. Besides some good results, this approach is not feasible in a smart TV watching scenario because each user has a diverse taste. Hence, the recommended items may become irrelevant for most of the group members. In aggregated models for preferences merging, the user profiles are merged for making a group profile. The items are then recommended to that particular 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 due to privacy leakages [3]. The exact identity of group members is still challenging due to privacy and security problems. By critically analyzing the literature, we argue that the existing recommender systems are neither efficient nor flexible enough to cope with problems of recommendations on a smart TV. Improving the recommender system for smart TV may not only contribute to user(s) satisfaction, but it may also enhance the conversion rate. The findings of this paper suggest that in a smart TV environment the recommender systems should recommend the right items to the right viewer(s) by considering the identity based on some nonvulnerable parameters, such as age, gender information, watching behaviour, and feedback.

This paper targets four significant issues. The first one is the identity of an actual member of a group and then recommend items accordingly. Second, the formation of profiles from actual user data, i.e. "age," "gender," and "number" in real-time. Third, based on user ratings, the identity of a dominant character in a group has been proposed. Fourth, this paper further proposes a statistical method for detecting a dominant character in a group based on the user's rating information. In this connection, this paper proposes a formula for a small number of groups and an age-gender matrix for larger members per group. For prototypical implantation, we used the smart TV capabilities for making personalized recommendations based on 'age,' 'gender,' and 'number of viewers' information. We used the camera and machine learning algorithms, such as Convolutional Neural Network (CNN) and Haar-Featured Cascade Classifier [20], [21] for the detection of "age," "gender," and "number of viewers" information and for generating individual and group profiles. The actual identity of a viewer is not considered for creating profiles so that to preserve the security and privacy of a viewer or group of viewers. By analyzing the results, we found that the group has a significant impact on supplying social metadata, such as ratings, tagging, and commenting.

This paper presents a robust recommender system by designing novel group modeling techniques, especially for smart TV viewers. The proposed recommender system works on smart TV by incorporating the features of user modeling, group modeling, information modeling, the context of use, and user behavior. A unique group modeling approach based on the age-gender matrix is suggested for group modeling. The group's information is then utilized for personalized services, including group recommendations. The contributions of this study are:

- A detail yet comprehensive discussion on the issues and challenges in the existing recommendation process, specifically from smart TV perspectives.
- The study proposed a novel method for precise and secure recommendations to the exact user(s) in front of a smart TV to mitigate the issues in predicting and calculating the user or group preferences.
- A novel formula and age-gender matrix have been proposed for user/group modeling based on 'age,' 'gender,' and 'number of viewers' information for helping in personalized content delivery to the exact viewer or group of viewers.
- The detection of a dominant character in a group has been achieved by utilizing user's ratings and statistical test, i.e. Z-test. Results show that the group has a significant impact on supplying social metadata.

- Lastly, the recommendation results are generated, evaluated, and found satisfactory.

The paper presents a more robust recommender system by taking the actual user data for user/group modeling to overcome the biases that occur due to predictions and estimations of the user's preferences. The age, gender, and number information are used as implicit feedback for the recommender system, which is well suited for smart TV watching scenarios. Improved recommendation results with greater user satisfaction have been achieved. The remainder of the paper is organized as follows: Section II presents related work regarding the proposed framework. Section III presents issues and challenges about recommendation systems, while Section IV provides details of the proposed methodology. Section V elaborates details of implementation and experimental setup regarding the proposed framework. The results, analysis, and discussion are provided in Section VI, VII. The study is concluded in Section VIII.

II. RELATED WORK

The smart TV is a connected TV that brings further challenges in the form of security, privacy, irrelevant recommendations, and interactive user interfaces [3], [16]. The relevant recommendations can enhance the conversion rate up to some extent, which in turn contribute to e-commerce and e-business [22]. Therefore, the appropriate and precise recommendations on smart TV may further contribute to not only user satisfaction [3], but also e-commerce. The highly interactive nature of smart TV is still reliant on traditional remote-control, which further creates issues in usability, searching, and browsing [3]. Therefore, relevant recommendations can play a significant role in mitigating these issues. The recommender systems use different techniques for generating groups, such as prediction models and preferences merging of individuals for generating group profile. In a study [23], a comparative analysis of group recommendation algorithms is carried out. The preference aggregation strategy is widely acceptable for group recommendation in a TV domain. However, this strategy is not feasible for smart TV viewers because the preferences merging may lead to privacy leakages. Moreover, the preferences of a kid are not viable to be combined with the preferences of a senior citizen. Véras, D. *et al.*, 2015 [24] briefly discussed the recommender system for TV-related content on the Web. However, relevant recommendations on smart TV and related issues in this connection are not discussed in detail. In the sub-sections, we categorized and discussed the most pertinent work on recommender systems, recommendations process, and algorithms from smart TVs/connected TVs perspectives.

A. RECOMMENDER SYSTEMS FOR SMART TVs

The delivery of personalized content on a smart TV is a difficult task [25] due to the reasons that smart TV is a non-personalized and lean-back device. Although, the smart TV may give better clues for recommender systems because of the internet protocol address, which is assigned upon connection. But the answer to "Who is currently watching the smart TV?" is still not found. The web-servers maintained a log file from which exciting patterns can be extracted [26], but in-depth analytics of user activities may further create privacy issues.

The recommender systems use different approaches, such as content-based filtering approach, collaborative filtering approach, and hybrid approaches [27]. The content-based filtering techniques use a user's history and the available content with an item [28], [29]. It analyzes the attributes of an item and user preferences, such as history, likes, and comments for recommendations [30]. The attributes of an item when matched with user preferences are recommended to that particular user [11]. In the case of a smart TV watching scenario, the content-based filtering techniques do not yield better results. The reason is that smart TV is a shared device and mostly enjoyed in groups. In such cases, smart TV is considered as a sole profile, which cannot represent the entire group or family [31]. The collaborative filtering techniques exploit the collective user's preferences and recommend items to a user having similar taste in the circle [24]. But detecting the most relevant circle is challenging because it relies on social metadata, which is not necessarily available for every viewer watching smart TV. The hybrid techniques combine both approaches for achieving better results (see Section III(B) for more details). Figure 1 depicts a general recommendation scenario on smart TVs.

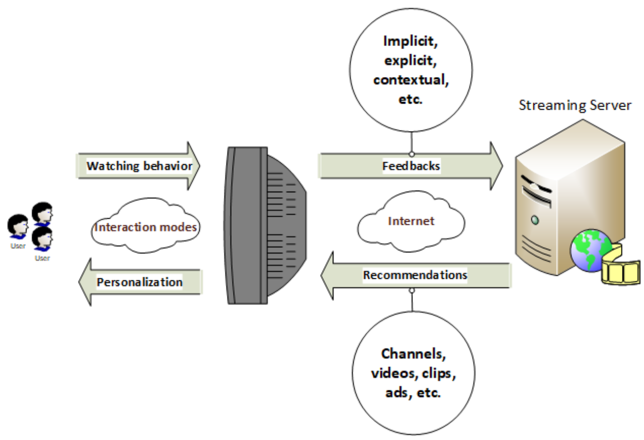

FIGURE 1. A process of recommendation on smart TVs.

In this paragraph, we discussed some Web-based recommender systems that use the viewer's social metadata, such as comments, likes/dislikes, ratings, etc., and recommend items accordingly. For example, MovieLens[i] is a web-based recommender system for movies recommendations, which invites users to rate a movie from the list. In return to the viewer's rating, the system predicts user interests and perform a personalized recommendation. However, from smart TV perspectives, these types of recommender system are least effective because tagging and ratings are among challenging

[i]http://www.movielens.org (access date: 08 Jan 2020)

activities to perform by using traditional remote control comes with a smart TV. Similarly, TV Predicator [30], is a web-based application that allows adapted recommendations to viewers without compromising the lean-back support in front of a connected TV. It utilizes the user's viewing behavior and feedbacks (explicit, i.e., ratings) on the server-side for predicting user's preferences and recommendations. However, predicting user's preferences and analyzing watching behavior by using data-mining and clickstream analytics may lead to severe privacy and security issues [32].

PolyLens [31], uses collaborative filtering techniques to recommend items to groups rather than individuals. It is a web-based recommender system for movies and works on the philosophy of collaborative filtering techniques for the group(s) of viewers. A detailed log file is used for deducing information about how viewers create a group(s). An empirical investigation from group users was conducted and analyzed for elicitation their experiences about their group recommendations. The PolyLens rely on collaborative filtering techniques, which is one of the main issues and challenges, specifically in a smart TV context. A hybrid approach is used in [24] and [30], for recommending TV programs. They developed *queveo.tv* (http://queveo.tv/),which is a Web 2.0 TV program recommender system. Besides the hybrid approach, the system provides all features of social networking, such as communication among users, adding and tagging contents, ratings, and comments. But all these activities are difficult to perform on a smart TV.

B. PROFILES FOR RECOMMENDATIONS ON SMART TV

The Hybrid Broadcast Broadband Television (HbbTV) [11] designed a framework that is divided into several sub-frameworks for the identification of viewer(s) in front of a connected TV. It also includes multi-users identification and recommendations, cloud-offloading, etc. It has built a Personal Recommendation Engine Framework (PREF) at the backend, which works on the philosophy of content-based filtering techniques, i.e., users rating, preferences, items, groups, characteristics, etc., [33]. The HbbTV is relying on content-based filtering techniques that recommend video as per user preferences [14]. The HbbTV can capture private, such as profile data, picture, watching behavior, etc., and hence criticized in the literature [13].

Similarly, the Personalized Electronic Program Guide (PEPG) is proposed based on user modeling and watching behavior [33]. They proposed a recommendation technique based on the user model and applied in the Personal Program Guide (PPG). The proposed model integrates different preferences, such as stereotypical information about TV viewers, explicit preferences of a user, and data viewing behavior. The explicit user preferences store the data produced by the user. The stereotypical information is collected from previous knowledge about TV-viewer categories. The viewing behavior is perceived by dynamic user modeling, which contains the user's preferences.

The smart parental advisory is proposed by a deep learning-based framework and usage control for supporting dynamic parental controls on a Smart TV [14]. The camera attached with a smart TV/connected TV was used for providing real-time parental controls on content. The content is provided based on age group, which is identified by using real-time face detection in front of the smart TV. However, the content delivered on a smart TV is limited to the delivery of video content based on the age group. The content recommendations on smart TV have been given less attention. Similarly, in [34], a recommender system based on face detection and recognition is proposed in on a smart TV. They used SkyBiomerty and Face++ for face detection and recognition, including emotion detection. In their work, they highlighted and tackled one of the core issues of the recommender system, i.e., cold-start problem. Moreover, they argued that the presence and detection of more than one person in a watching room can form a group and hence the recommender system should consider this information to recommend items to the group of viewers instead of individuals. They used average without misery strategy for group recommendation.

TV content recommendations based on a user's profile merging techniques for group viewers is proposed [35]. The profile merging technique is based on total distance minimization approach for achieving better recommendation results. The RecTime [36] proposed a real-time recommender system for online web-based broadcasting services. It considers the time factors and user's preferences concurrently for the recommendation process. They developed a new recommendation algorithm, which captures the user's status as well as the status of the broadcasting shows. Shin and Woo [37], proposed a smart TV-based automatic personalized recommendations of TV programs. They used Sequential Pattern Mining techniques to analyze a viewer's watching behavior. They argued that searching for the desired program is difficult due to massive collection hence worked on the automatic recommending of TV programs. The work done is only related to the TV program content [12]. Kwon and Hong [38] proposed collaborative filtering based and novel similarity method TV Program Recommender System (PRS) for personalized content delivery on smart TV/connected TV. The proposed techniques were developed for the recommendation performance of Electronic Program Guide (EPG) on smart TV and robust against the cold-start issue. The method provides user-centric PRS by explicit preferences based on the prediction of ratings for non-viewed programs.

C. ONTOLOGY-BASED RECOMMENDER SYSTEMS FOR SMART TV

An ontology-based recommender system [39] for recommending TV programs on a smart TV is presented by constructing a TV program domain ontologies. They proposed a similarity matching technique to mitigate the issue of information overload. The authors claimed that content-based similarity matching based on program ontology could yield better recommendation results than rating-based techniques.

Similarly, OntoTV [40] proposed a technique for the organization of TV-related contents from different sources. It is a television-related content management system, which retrieves information about contents from various sources and characterizes them using knowledge engineering and different ontologies. Similalry, Kim *et al.* [41] proposed contents and viewers' ontologies for searching and recommendations of TV programs. They developed ontologies of TV programs for defining the semantic structure of the different contents. Comparatively, they achieved more precise and better results than keyword-based searching, especially for documentary programs.

D. SOCIAL METADATA FOR RECOMMENDATIONS ON SMART TV

The smart TV supports the Web 2.0 features that enable a viewer to comment, writing blogs, likes/dislikes, etc. Although, use of social networking sites on a smart TV is not a regular activity; yet, it has full support for every read/write web activity. A multi-agent TV recommender system [42] is proposed for TV viewer(s). it considers three types of user information, i.e., history, preferences, and feedback, and then generates recommendations for a viewer. It works by operating three agents, i.e., implicit recommender agent, feedback agent, and explicit recommender agent. These agents work on a user profile and recommend programs to viewers. Table 1 shows some existing web-based systems for recommending TV-related multimedia content to a viewer(s).

Chang *et al.* [46] proposed a system that integrates the Web 2.0 features into set-top-boxes and smart TVs for enhancing recommendation results. The proposed framework is based on analyzing TV program information, user profile, and user preferences for producing appropriate and precise recommendations on smart TVs.

Summarizing the literature, we can conclude that existing recommender systems for smart TVs are not efficient nor flexible enough to cope with issues of recommendations and personalization services, specifically to a group of viewers. By analyzing the existing literature, we argue that besides recommendations and personalization services, the recommender system should consider the privacy and security of the viewer(s). Moreover, the recommender systems should grow as per user dynamic interests. We further argue that adding rich contextual information may recommend items in a better way than existing techniques.

III. ISSUES AND CHALLENGES

The recommendation is a client-server process, in which the server rely mostly on client behavior for relevant and precise recommendations. In case of smart TV, the activities and watching behavior are different from other devices, which creates hurdles in the recommendation process. In subsections, we highlighted the issues and challenges from both client-side (smart TV) and the server-side.

TABLE 1. Existing recommender systems for recommending TV related contents.

Study/ System	Purpose	Advantages/ Features	Disadvantages in the Context of Smart TV
RecTime [36]	• Real-time recommender system based on Time factor and preferences	• Recommendations based on • Time • Preferences	• Considers only a single-viewer preference • However, smart TV is a group and shared device
TV-Predicator [30]	• Personalized program recommendation on smart TV	• Collaborative Filtering techniques for predicting rating • Content-Based Filtering techniques for item's similarity • Clustering techniques for enhancing performance	• Smart TV is a group and shared Without actual person detection, personalized recommendations are not viable
OntoTV [40]	• Ontological approach for content collection	• Television content Management System • Retrieve television contents and present them using knowledge and ontologies	• Single profile-based recommendations • However, smart TV is a group and shared device
CPRS [43]	• Channel recommendations for the group having similar taste	• Determine the user's watching behavior patterns in the TV program from EPG • Then build a program recommendation system	• Single profile-based recommendations, • However, smart TV is a group and shared device
HbbTV [44]	• To play the smart TV features as a browser overlay on TV channels	• Multi-user recommendations • Synchronization between media • Multi-user identification, • User-centred reputation scores for applications • Cloud-offloading.	• Privacy issues • Preferences merging • Cannot handle the diverse interests of individuals
Queveo-TV[ii]	• Recommendations using social data	• Recommendations based on hybrid approaches with social data integration	• Socializing is a rare activity on smart TV
AIMED [45]	• A TV Recommender System based on (AIMED)	(AIMED) • Activity • Interest • Mood, • Experience • Demographic information	• Frequent switching in front of a smart TV • Such a system cannot predict the exact activity, interest, mood, experience
YouTube[iii]	• A video service provider	• Recommendations based on implicit and explicit feedback	• As smart TV is a group and shared device so frequent switching is neither detectable nor considered by YouTube
Personalized Program Guide [33]	• Personalized program Guide (PPG)	• Explicit user information, • Stereotypical viewers information, • Viewing behavior	• Designed for a single viewer

TABLE 1. ***(Continued.)*** **Existing recommender systems for recommending TV related contents.**

PolyLens [31]	• A group recommender system for web users	• Based on collaborative filtering techniques	• The groups are formed based on collaboration • However, smart TV is enjoyed in closed groups
MovieLens[iv]	• Recommend movies based on user preferences	• Collaborative Filtering Approaches for recommendations	• Ratings/tags are rare activities on smart TV
Netflix[v]	• A video service provider	• Recommendations based on implicit and explicit feedback	• Single profile-based recommendations, • However, smart TV is a group and shared
GroupLens[vi]	• Recommendation based on user preferences	• Recommender systems and Social computing	• General-purpose system for web users

A. ISSUES FROM SMART TV PERSPECTIVES

Millions of households have shifted from legacy TV systems to smart TVs for watching and streaming web-based content, such as live channels, video, audios, and other web-related content [47]. Resembles with traditional TV systems, smart TVs are also lean-back supported devices and generally used for viewing video, movies, and clips on the large screen [3]. Hence, the expected feedback from smart TV viewers cannot be compared with the feedback come from a smartphone or computer user. The web applications, including social networking sites, focus on personalization. All activities a user performed are tracked and recorded for a personalized recommendation. Web-based contents are recommended based on profile information, watching history, likes/dislikes, and comments. Thus, the contents of the web are recommended for individuals, which may not be relevant to closed groups or the whole family.

Predicting, maintaining, and updating 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, such as profile generation, profile merging techniques, face detection, and recognition systems, data mining techniques, etc., have been used for personalized recommendations. However, such methods may lead to privacy and security issues [48]. Some recommender system uses social metadata, such as likes, dislikes, blogging, commenting, etc., for refining the recommendation results. However, using the Web 2.0 features are among unusual activities on smart TV [3]. Moreover, surfing the Web 2.0 features by using a traditional remote control is a laborious job. As discussed, smart TVs are mostly used for viewing movies and videos on a large screen [1], [49].

A smart TV User Interface (UI) demands more interaction, which is not welcomed by the viewers. A clutter UI makes it hard to open the desired channel [50] or selecting the recommended items [16]. The channels are represented by the software application in a smart TV, which streams different content from the channel's servers [49]. Thus, the items are recommended within the running app. For instance, YouTube videos are recommended within the YouTube app running on a smart TV. Other content, such as books, textual news, etc., has nothing to do with YouTube's recommender system. Therefore, any app (channel) with a better recommender system may recommend objects in a better way. Netflix and YouTube have different algorithms for recommendations [50]. It should be noted that on smart TV's UI, switching between channels is switching between apps, which is not an easy task on the traditional remote control available with smart TVs [3].

B. ISSUES FROM RECOMMENDER SYSTEMS PERSPECTIVES

The recommender system uses three approaches, i.e., content-based filtering, collaborative filtering, or hybrid approaches. The collaborative filtering techniques recommend items based on user's feedback. The feedback can be implicit or explicit [51]. The explicit feedback required explicit actions from a user, while implicit feedbacks are produced by the recommender systems itself [52]. The explicit feedback on a smart TV is a difficult job because of legacy remote-controls. Moreover, secondary activities, such as commenting, liking/disliking, etc., on a primary interaction device, i.e., remote control, is a difficult task [38]. Therefore, from smart TV watching perspectives, implicit feedback generates improved results than explicit feedback [44]. Furthermore, the collaborative filtering techniques depend upon other users' data, which is sometimes not available, and hence we cannot expect good recommendation results [45]. Collaborative filtering techniques have issues, such as the cold-start problem, data sparsity [53], grey sheep problem, scalability problem, synonym problem [26]. To overcome the issues of the cold-start problem in smart TV scenario, the Top-N algorithm, which is a non-personalized algorithm, recommends the top-most rated items to a user [54].

The Content-based filtering technique compares program attributes (item description) to a user profile; after which, the recommender system makes similarities among them [45]. Based on comparisons, the appropriate programs (items) are recommended to a user. It uses likes, dislikes, comments, history, and descriptions with an object and recommends the most appropriate items. When a user profile matched with the description of an item, an item is then suggested to a user [55]. Content-based filtering suffers from over-specialization [45]. The problem with content-based

[ii] http://queveo.tv/ (access date: 08 Jan 2020)
[iii] https://www.youtube.com/ (access date: 08 Jan 2020)
[iv] https://movielens.org/ (access date: 08 Jan 2020)
[v] https://www.netflix.com/pk/ (access date: 08 Jan 2020)
[vi] https://grouplens.org/ (access date: 08 Jan 2020)

filtering techniques is that smart TV is considered as a sole profile (i.e., personalized) device like a smartphone or computer. However, in most homes, smart TV is watched by the closed group member or entire family [56]. Thus, a smart TV-based profile cannot be the accurate representative of the entire group/family [57], [58]. In content-based filtering technique, a user profile and an already spent contents play an important role in the recommendation process. They hence could fail to produce better and appropriate recommendation results. Table 2 shows some existing recommendation approaches and algorithms in the context of smart TV.

TABLE 2. Existing recommendation methods in smart TV context [3].

Recommendation Methods	Approaches	Some common algorithms	Remarks
Collaborative filtering techniques	Shared preferences of the crowd	Pearson-correlation, Singular Value Decomposition (SVD), Slope one, Cosine similarity	Most of the secondary actions, i.e., likes, dislikes comments, etc., are infrequent activities on smart TVs
Content-based Filtering Techniques	user profile and Item's description,	Neural network, decision tree, Cosine Similarity, clustering algorithms, Bayesian network,	Smart TV is a shared device. typically enjoyed in groups
Hybrid Filtering	Combination of both approaches	Merging two approaches	Inherits the similar issues of both methods
Contextual Recommendations	Time, location, Events, Place	Contextual ontologies, Contextual rules,	Rich set of contextual information can be explored further
Ontological-based (Semantic-based)	Ontologies, Semantic Rules	SWRL Semantic Similarity Metric,	Domain specific ontologies

Moreover, the viewing history cannot be associated to every individual in a family or group members. Although some work have been done on combining time factors with watching history; yet, in the context of a smart TV, predicting the exact number and type of audiences from history (consumed contents) is not yet achieved.

IV. PROPOSED METHODOLOGY

We proposed a novel recommender system for secure and relevant recommendations on smart TVs by using a real-time profile generation approach, including virtual group profiles. We used the built-in capabilities of smart TV, i.e., processing, camera, and storage. For relevant and secure recommendations, most of the primary work, i.e. "age," "gender," and "number" extraction from viewers face(s) is done on a smart TV. First, the individual users were sat in front of smart TV, and their watching behavior was recorded and saved as profiles on the smart TV. After this, as per our group modeling techniques, i.e. formula for generating groups was used along with their watching activities for every possible combination of group and saved as group profile(s) on the smart TV. These individual and group profiles and watching activities are used for recommendations. The information is extracted without storing any vulnerable information about a user, such as a picture, name, location, etc. The schematic diagram is shown in Figure 2, which consists of different modules.

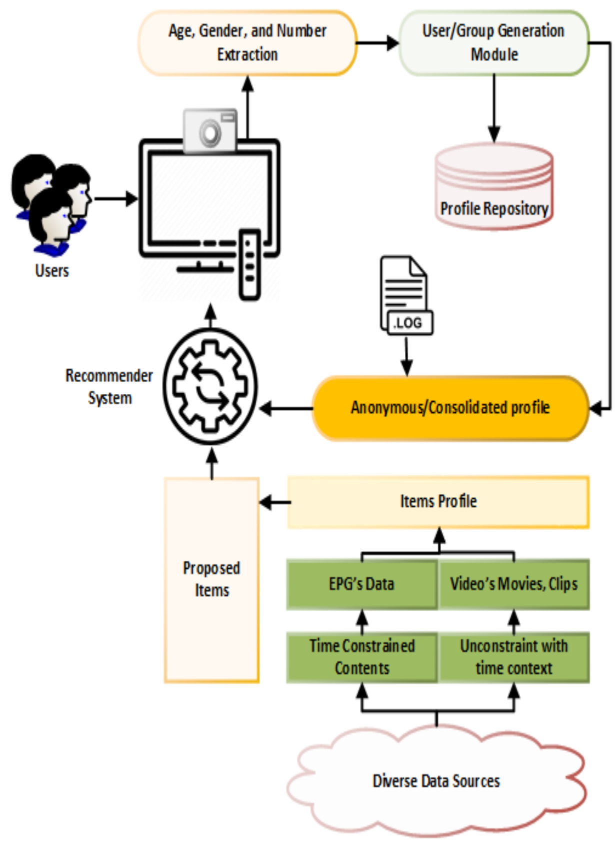

FIGURE 2. Schematic diagram of the proposed system.

A. SYSTEM ALGORITHM

The overall system is represented in Algorithm 1. The system starts by detecting the faces in a watching room from live streaming, in which the system counts the number of faces, extract age, and gender information. The smart TV detects the "*age,*" "*gender,*" and "*number*" information from the live streaming of viewer's faces. After the detection of faces,

Algorithm 1 Overall System & Recommendation Process

1. **Input:** Detect Number of faces *N*
2. If N=1,
3. Detect the age information *ag*
4. Detect the gender information *G*
5. Go to step 11
6. Else
7. Detect the number of viewers *V*
8. Detect the age information *ag*
9. Detect the gender information
10. Form groups G, where $G = 2^n - 1$ *or use age-gender matrix*
11. Generate Anonymous profile *P, where P= (a,b,c,d, ab,...... abcd)*
12. Detect profile repository, i.e., history
13. Extract item(s) data from time-constrained channels, i.e., EPGs
14. Extract item(s) data from video sharing websites
15. Repeat extraction from diverse data-sources
16. Generate proposed item list *T*
17. Match with anonymous user/group profile *P*
18. Detect item(s) profile T
19. **Output:** Recommend items *T* to profile P
20. **Repeat:** For each face detection *N+1 or N−1*

the user/group generation module is activated, which generates an anonymous and consolidate profile(s) for the individuals and group viewers. On the other hand, the recommender system generates and activates the item's profile. The item profile is built from stored videos, live channels, EPG's data, etc. Based on user/group profile information and items profile information, a suitable item is recommended to the viewer(s) in front of smart TV.

B. PROPOSED GROUP GENERATION TECHNIQUES

We proposed two novel approaches for generating real-time anonymous profiles, including group profiles based on "age," "gender," and "number" information. This approach creates individuals and group profiles from the actual data. It does not rely on estimations, predictions, or any vulnerable information for finding the actual group members. The procedure is explicitly suited for smart TV watching environments due to the reasons that smart TV is now a computing gadget. In the sub-sections, we discussed both approaches in detail.

1) FORMULA APPROACH

The family members per household are different in every region of the world. Generally, the average number of members per household is ranging from 2.1 to 5.9, i.e., from 2-6 [59]. The $P_r = 2^n - 1$ formula shows the possible combination of profiles, where P represents the profile and *n* is the number of people in a family or group. Considering an example of average users, i.e., four family members, Figure 3 depicted the possible number of profiles, including individual and group profiles. Based on this approach, the total number

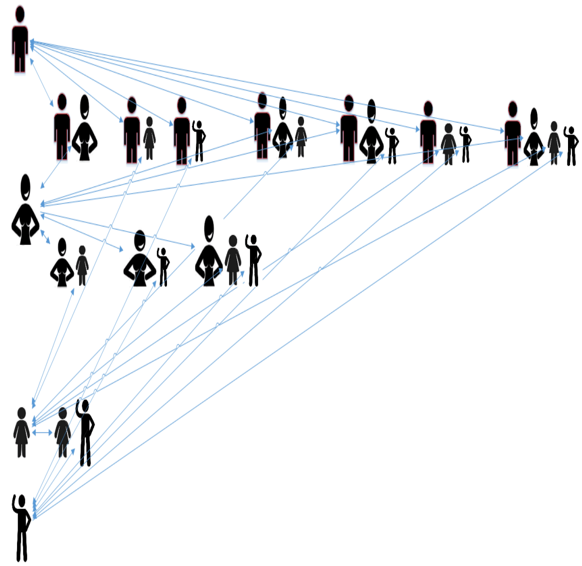

FIGURE 3. The possible number of profiles for a family of four members.

of profiles (4 individual + 11 group profiles = 15) can be generated for a family of four members, as shown in equation (1). The A, B, C, D are the imaginary characters where A represents the father, B represents mother, and C, D represents the two kids.

An individual user profile may be {A, B, C, D}, whereas group profiles may be {AB, AC, AD, BC, BD, CD, ABC, ABD, ACD, BCD, ABCD} as calculated in equation (1) i.e. P_r.

$$P_r = 2^n - 1 = 2^4 - 1 = 16 - 1 = 15 \tag{1}$$

where P_r represents the total number of profiles and *n* is the number of people in a family or group. For a family of four people, we have the following number of possible profiles: $P_r : \{A, B, C, D, AB, AC, AD, BC, BD, CD, ABC, ABD, ACD, BCD, ABCD\} = 15$ where

$$\text{single Users: } \left\{\begin{matrix} A \\ B \\ C \\ D \end{matrix}\right\} = 4$$

$$\text{Groups: } \left\{\begin{matrix} g1\{AB\} \\ g2\{AC\} \\ g3\{AD\} \\ g4\{BC\} \\ g5\{BD\} \\ g6\{CD\} \\ g7\{ABC\} \\ g8\{ABD\} \\ g9\{ACD\} \\ g10\{BCD\} \\ g11\{ABCD\} \end{matrix}\right\} = 11$$

Figure 3 depicted the total number of profiles, that can be generated for a family of up to four members.

2) AGE-GENDER MATRIX APPROACH

Senot *et al.* [60], worked on forming groups by TV consumption data. However, the viewer's detection based on consumption/viewing data may produce irrelevant results. Similarly, in a study [61], some work has been discussed, in which they focus on the dominant and social influence of a group member. However, the actual members and satisfying each member is still challenging, which we have tackled in this paper up to some extent. For larger families/group, i.e. more than 4, We proposed the age-gender matrix for generating virtual group profiles.

The proposed formula approach is well suited for small member up to four. Applying the formula approach for more than four members per family/group will generate a large set of groups that is not feasible because detecting and maintaining such larger groups will be a huge problem even for the machine, i.e., smart TV. Therefore, in the case of more than four people per group, we proposed an age-gender matrix, as shown in Tables 3 and 4. By the Age-Gender matrix, we can create groups based on age and gender information. This Age-gender matrix may help in creating the groups and then generate an anonymous and consolidated virtual group profile for the recommendation process. The Age-gender Matrix consists of ages and gender information is shown in Table 3. Column A (Male) age starts from 21-30 up to >60. Similarly, the column-B (Female) starts from 21-30 and up to >60. It means that both these columns (A and B) represent the young/senior members of a home. Similarly, column-C (Male) age starts from 1-10 up to 11-20, whereas the column-D age starts from 1-10 and up to 11-20, which means these two columns (C and D) represent the kids and other junior members of a family. Now, in case of six persons and their ages detected as shown in Table 3. The possible number of group member based on age information may be ABCD= {(AB, A, CD)}, where AB is from same age group with different gender information, A is distinct group member with age >60, and CD is from different age groups with a different gender.

We can assign weights to determine the dominant group of people, which may provide input to the recommender system. Therefore, AB=2 (blue color), CD=3 (yellow color), C=1 (pink color), and A=1 (green color). Now, the recommender system may recommend items based on the preferences of either CD or AB, which may satisfy the whole group in a better way. Similarly, the six persons are detected and shown in Table 4. The possible number of group member based on age information may be ABCD= {(A, B, C, D)}, where A=2 (green color), B=1 (yellow), C=2 (blue), and D=1 (pink). In this case, the dominant members of a group may be A and C. The recommender system may recommend items based on the preferences of the dominant group member that may satisfy the whole group.

TABLE 3. Proposed age-gender matrix for gender-based grouping.

Age Gender Matrix				
Age	A (Male)	B (Female)	C (Male)	D (Female)
(1-10)			*	*
(11-20)			*	
(21-30)				
(31-40)	*	*		
(41-50)				
(51-60)				
>60	*			

TABLE 4. Proposed age-gender matrix for age-based grouping.

Age Gender Matrix				
Age	A (Male)	B (Female)	C (Male)	D (Female)
(1-10)			*	*
(11-20)			*	
(21-30)				
(31-40)	*	*		
(41-50)				
(51-60)				
>60	*			

V. IMPLEMENTATION AND EXPERIMENTAL SETUP

The proposed methodology is implemented on smart TV with an attached camera and tested by different families consist of up to four members for analyzing the results. As the members per family are up to four, therefore we used only the proposed formula approach for analysis. For prototypical implantation, we used the smart TV capabilities for making personalized recommendations based on *"age," "gender,"* and *"number of viewers"* information. We used camera and machine learning algorithms, such as Convolutional Neural Network (CNN) and Haar-Featured Cascade Classifier [20], [21] for the detection of *"age," "gender,"* and *"number of viewers"* information for generating individual(s) and group profiles. The "age," "gender," and "number" information are collected from the live streaming of camera attached with a smart TV for generating groups. A separate profile is generated for each group instead of merging the individual profiles or preferences. We used the imaginary characters, i.e. A, B, C, D for each member of a family, where A represents the father, B represents mother, and C, D represents the kids as shown in Figure 3. The "age," "gender," and "number of viewers" information was detected from a live recording of faces of the viewers by using a camera attached to a smart TV. The details of such user logs and timing information for one month are depicted in Table 5. Analyzing Table 5, we found that most of the groups are

TABLE 5. User and interests detected for one month.

Week Days	Days	7:00 AM	9:00 AM	11:00 AM	.....	.....	3:00 AM	5:00 AM
Monday	1	B		A		AC		
Tuesday	2	A			AC			
Sunday	14		D	CD			D	
.....	.....	.....	.....	.....	.....	.....	.....	.....
Tuesday	30			AD	CD	C		

formed at nighttime. It is because, in this specific region, most of the family members are gathered at nighttime.

A. USER IDs MAPPING

The user IDs in the generated dataset were mapped for four family members, which makes 15 profiles per family as {A=1, B=2, C=3,……, ABCD=15}. The mapping process is used for predicting the ratings and then recommending the items based on collaborative filtering techniques. After mapping these 15 profiles, we have 1426 watching and rating activities for different movies shown in Table 6. The ratings of these are analyzed statistically and experimentally using the GraphLab framework [62].

TABLE 6. Dataset information for 15 users.

File names	Watched activities	File type
Tags	1426	.CSV
ratings	1426	.CSV
movies	8532	.CSV
Links	9742 links of movies to IMDB database	.CSV

B. USER-ITEM MATRIX

The user-item matrix shown in Table 7 shows the records for capturing data for one day, i.e., 24 hours. We used this matrix for logging the user activities for one month. The movie-IDs are taken from MovieLens dataset. We captured and

TABLE 7. User-item matrix.

User(s)	07:00 am	9:00 am	11:00 am	01:00 pm	03:00 pm	05:00 pm	…	05:00 am
A			-				…	
B	**1**						…	
C							…	
D							…	
AB							….	
AC					**3**	**47**	…	
⋮							…	
ABCD							…	

logged user(s) information along with watching history. The captured information is fully compatible with the MovieLens dataset.

VI. RESULTS AND ANALYSIS

The logged data on smart TV has been pre-processed and cleaned for experimentation. The watching activities of the four members of different families/groups were logged for one month. The recorded files were kept similar to the MovieLens dataset. Some manual efforts were also made for mapping and cleaning of data. A total of 110 (on average) activities were recorded for each user, i.e., user A, user B, user C, and user D, including group users, i.e. (AB, AC, AD, ……. ABCD). For making results unbiased, we logged the user watching history in the same manner as MovieLens do. The four files, which come with Movilen's small dataset, i.e., *'links,' 'movies,' 'ratings,'* and *'tags,'* were used for logging the information in our dataset. The *'movie,' 'title,'* and *'genre'* of movie files were kept the same as in the original dataset. Similarly, the *'movieid'* was kept the same as in the original dataset. This file further contains *'userid,'* to which we assigned numerical numbers, i.e., 1 for user A, 2 for user B, 3 for user C, 4 for user D, 5 for AB (group 1 user), etc. The *'tag'* column in the tags file for each watched movie was kept the same as in the original dataset.

A. IMPROVED RATINGS BY THE PROPOSED VIRTUAL GROUPS

The average ratings given by different users have been calculated for movies (items). The average ratings given by the user (A) is 4.22/5, 3.93/5 by the user (B), 4.26/5 by the user (AB), and so on. The improved ratings for the group user (AB) show that group profiles have better ratings than individual profiles, which in turn improve the recommendation results.

B. DETECTING A DOMINANT CHARACTER FROM USER RATINGS

The differences between individual user's ratings and group user's ratings are evaluated statistically. Results show that the difference is significant and, therefore, will affect the recommender systems relying on user ratings. The Z-test was used for finding the mean differences between individual ratings and group ratings. The ratings of a user (A) and group user (AB) have been tested statistically using Z-test. Results show that the p-value (0.740) is greater than the alpha value (0.05), which shows a significant difference between the ratings of the individual user (A) and group user (AB). Similarly, the ratings of the user (B) and group user (AB) have been tested statistically using Z-test. The results show that p-value (0.008) is less than the alpha value (0.05) indicates that there is no difference between the means of ratings given by the user (B) and ratings given by group user (AB).

An interesting statistic has been yielded by comparing the ratings of individual users and ratings of group users. The dominant character in a group can be found by finding the mean differences between the ratings given by different users, either individually or in a group. As discussed, there are significant differences between the mean ratings assigned by the user (A) and ratings given by the group user (AB). It means that the group decision will not be influenced by the user (A). Therefore, in this small group user, i.e. (AB), the (A) character is not dominant. Similarly, there are no differences between the means of ratings given by the user (B) and ratings given by group users (AB). It shows that user (B) is more dominant and will have an impact on the group decisions.

C. PROPOSED GROUP PROFILES VS SOCIAL THEORY CHOICE

The proposed group profile has been compared and analyzed against the social theory choice for group recommendations [63]. In the following sub-sections, the normalized group profiles are compared with the profiles that are estimated and created from social choice theory.

1) ADDITIVE UTILITARIAN STRATEGY ANALYSIS

In this strategy, the ratings of all users are added, and then the highest rating items are ranked for the recommendations. The ratings given by the user (A) is added with the ratings given by the user (B). The ratings of group user (AB) is multiplied by 2 for making them normalized. Figure 4 shows that recommendation through additive utilitarian strategy by the group user (AB*2) is producing better recommendations than adding/merging the ratings of the user (A) and user (B).

2) MULTIPLICATIVE UTILITARIAN STRATEGY ANALYSIS

In this strategy, the ratings of the user (A) is multiplied with the ratings of the user (B), and then the highest rating item is recommended. The ratings of the group user (AB) is multiplied with itself, i.e. (AB^2) for making them normalized.

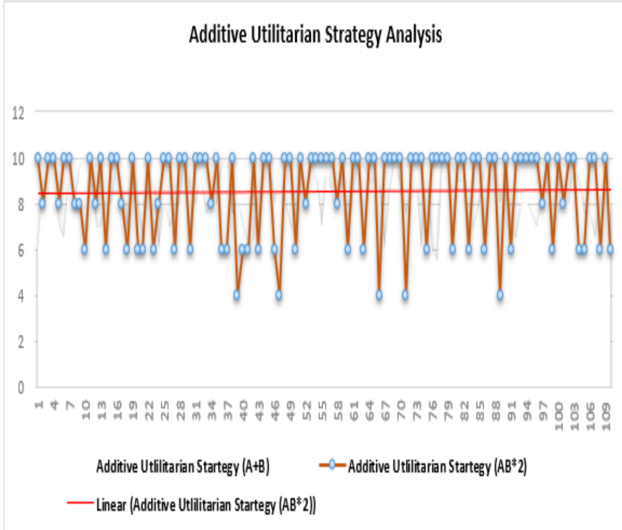

FIGURE 4. Comparing additive utilitarian strategy.

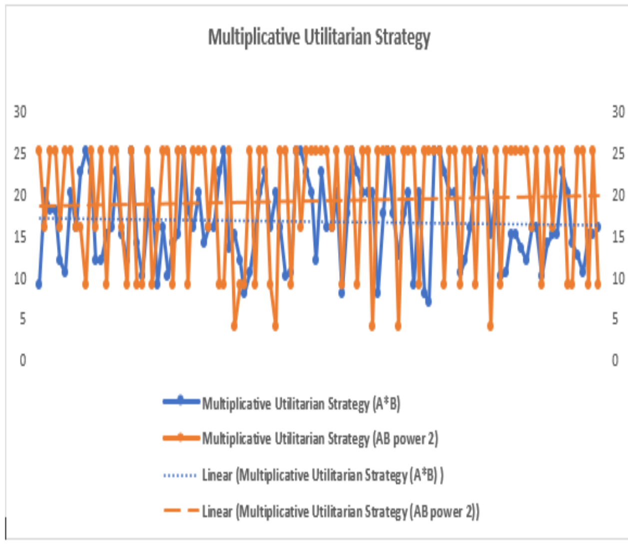

FIGURE 5. Comparing multiplicative utilitarian strategy.

The results are shown in Figure 5. Compared with the multiplicative strategy for the user (A) and the user (B), we found better and consistent ratings given by the user (AB), which is a group user.

D. EXPERIMENTAL RESULTS

We also evaluated the logged data by using GraphLab-Create framework [62], which supports several machine learning models, including recommender system models. The GraphLab framework is developed at Carnegie Mellon University. The reason for choosing GraphLab-Create is its scalability and parallel framework support for machine learning [62]. We used Python language for installing

GraphLab-Create framework. The GraphLab-Create supports Python 2.7, which we have installed from Anaconda (https://www.anaconda.com/distribution) distribution. The dependencies, such as Pandas, and NumPy were also installed. Python's NumPy and Pandas library were used for finding some deep insights in our dataset. The dataset is fetched to the GraphLab framework. For scalability purposes, we used Pythons' SFrame[vii] techniques. After fetching the dataset, the recommendation model was created. We used the Ranking Factorization Model for testing the desired results, as shown in Figure 6. A Ranking Factorization Model learns from latent-factors for each user and item and then rank this information for the recommendation process [64], [65].

1) IMPROVED RECOMMENDATION SCORES

The scores of all users are visualized in Figure 6, which shows that the ratings for group users are better than individual users. It further clarifies that the group has a significant impact on supplying social metadata, such as rates, tags, comments, etc. The groups based on age and gender information can produce better results than groups formed based on predictions and estimations.

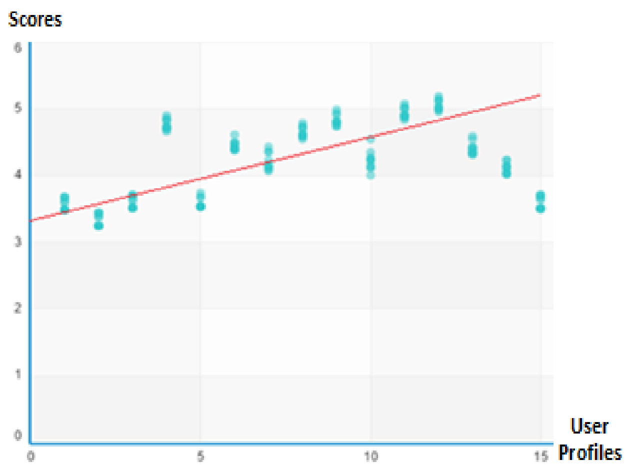

FIGURE 6. Trendline of user's scores.

2) BETTER PRECISION, RECALL, AND F-SCORE

The user data has also been tested by an already trained dataset provided by the MovieLens. The original test-data of MovieLens was replaced by our generated dataset. We select the popularity model for recommending items against the trained dataset. The higher precision and recall show better recommendation performance. The precision, recall, and F1-score are calculated by equation (2) equation (3), and equation (4) respectively [66].

$$\text{Precision (P)} = \frac{\sum |R_r \cap T_u|}{\sum |R_r|} \tag{2}$$

[vii]https://pypi.org/project/SFrame/

$$\text{Recall (R)} = \frac{\sum |R_r \cap T_u|}{\sum |T_u|} \tag{3}$$

$$F1\text{-Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{4}$$

In equation (2) and (3), the R_r is the recommendation results, and T_u is the set of user's favorite items. To find the best blend of recall and precision, we calculated the F1-Score by equation (4), which is the harmonic mean of both precision and recall metrics. In equation (4), we used precision and recall values for calculating F1-Score. The precision, recall, and F1-score for each user has been calculated, as shown in Figure 7. The F1-score for first four users are more closed to recall and climbing towards precision when more members are added to the group profile.

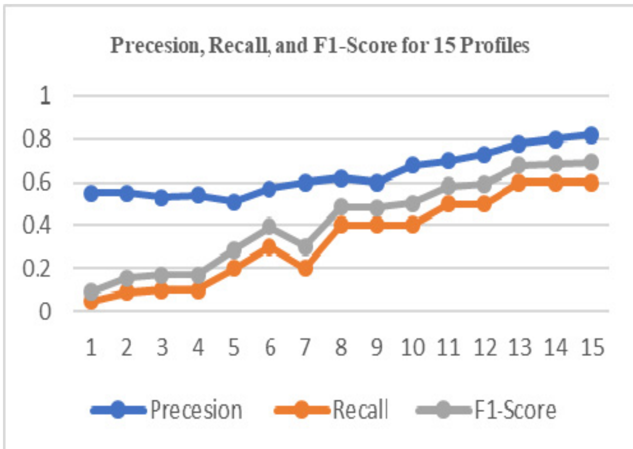

FIGURE 7. Precession, recall, and F-score.

VII. DISCUSSION

In this paper, we tackled four significant issues. First, we used the actual user's data, i.e. "age,", "gender,", and "number" of viewers for the formation of groups to get rid of the issues raised from predictions and estimations of user's preferences. Second, we proposed novel user and group formation techniques for generating uniformed and biased-free groups. Third, we proved that the group has a significant impact on decisions and supply of social metadata, i.e., comments, ratings, likes/dislikes, etc. Fourth, we calculated and detected a dominant character in a group from the user's ratings. We formed groups from actual viewers "age," "gender," and "number" by using the real-time approach. We proposed different combinations of groups using a formula for four family members and a proposed age-gender matrix for more than four members of a group. We used the built-in capabilities for extracting such information and for making real-time profiles. Different families; consist of up to four members have tested the prototypical implementation. We achieved good recommendations for individuals and group viewers. There is no estimation or prediction involve for generating the profiles in front of a smart TV. The cold start issue has been handled by capturing real-time data from users. Based on the user's ratings, we detected a dominant character in a group. Moreover, enhanced ratings have been observed, which show that the group has an impact on the delivery of social metadata. Furthermore, the formation of grouping from actual data has been resolved without estimation or predictions.

VIII. CONCLUSION AND FUTURE WORK

This study aimed to generate and maintain anonymous, secure, and consolidated user profiles, including individual and group profiles on a smart TV. The smart TV provides built-in capabilities, which we used for generating real-time yet secure profiles. We used the "age," "gender," and "number of viewers in a group" information for creating not only individual profiles but also group profiles. The results are analyzed statistically and experimentally by using different tests and algorithms. The results showed a significant impact on recommendations to individuals and group users. Based on the user's ratings, this paper further proposed a statistical method for finding a dominant character in a group. By using the proposed approach, a dynamic and robust recommender system can be achieved. Concluding the paper, we argue that existing recommender systems are neither flexible nor intelligent enough to cope with the varying interests of smart TV viewers.

During testing the prototype, we found some limitations. For example, the proposed work is not suitable for smart TVs that are used in public places like hostels, restaurants, roadsides, etc. Low Brightness was also an issue in the accurate detection of the viewer's *"age," "gender,"* and *"number"* information.Moreover, the effect of distance between a smart TV and the viewer(s) was also observed. In the future, we intend to extend this work by adding more contextual information, such as time of the day, days of the week, weeks of the months, local and international events, etc. We further aim to use the proposed user/group modeling approaches for the contextual recommendations of advertisements (ads) on a smart TV. The best solution would be to bring the ads of interests to the watching rooms.

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