

Research Article

ROPPSA: TV Program Recommendation Based on Personality and Social Awareness

Nana Yaw Asabere  and Amevi Acakpovi 

Accra Technical University, Accra, Ghana

Correspondence should be addressed to Nana Yaw Asabere; yawasabere2005@yahoo.com

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The rapid growth of mobile television (TV), smart TV, and Internet Protocol Television (IPTV) content due to the convergence of broadcasting and the Internet requires effective recommendation methods to select appropriate TV programs/channels. Many previous methods have been proposed to address this issue. However, imperative factors such as the utilization of personality traits and social properties to recommend programs for TV viewers remain a challenge. Consequently, in this paper, we propose a recommender algorithm called Recommendation of Programs via Personality and Social Awareness (ROPPSA) for TV viewers. ROPPSA utilizes normalization and folksonomy procedures to generate group recommendations for TV viewers who have common similarities in terms of personality traits and tie strength with a Target TV Viewer (TTV). Therefore, ROPPSA improves TV viewer cold-start and data sparsity situations by utilizing their personality traits and tie strengths. We conducted extensive experiments on a relevant dataset using standard evaluation metrics to substantiate our ROPPSA recommendation method. Results of our experimentation procedure depict the advantage, recommendation accuracy, and outperformance of ROPPSA in comparison with other contemporary methods in terms of precision, recall, f -measure ($F1$), and arithmetic mean (AM).

1. Introduction

Globally, recent decades have witnessed the emergence of novel challenges regarding television (TV) content consumption. TVs are machine screens that broadcast signals and convert them into multimedia pictures and sounds for educational and entertainment purposes. The evident convergence of Internet and broadcasting has paved the way for the proliferation of different TV technologies such as Internet Protocol TV (IPTV), mobile TV, and smart TV which can be viewed on multiscreen and device ecosystems [1–6]. In particular, the content of mobile TV is watched through mobile phones and smartphones, which makes them digitally ubiquitous.

Additionally, online social networking sites such as Facebook, Netflix, YouTube, and Twitter have complemented TV viewing experience by creating a large number of multiscreen applications [1–3]. Internationally, due to habit changes in accordance with diversification of

TV content, active viewers experience difficult times deciding which programs to watch among thousands of channels as shown in Figure 1. Such situations create difficulty for TV producers to predict viewers' interests and preferences in certain circumstances [1–6].

Consequently, the identification and selection of TV programs/channels have improved over the years. Electronic Program Guides (EPGs) have become available and more appropriate to use in comparison to historical and traditional methods such as browsing printed program guides and channel surfing [8–11]. Intelligent personalization techniques and systems can be innovatively utilized to significantly improve the effectiveness of searching and retrieving TV programs of interest.

Many researchers such as [1–6, 8–11] have utilized traditional recommender systems and techniques such as hybrid filtering (HF), collaborative filtering (CF), and content-based filtering (CBF) as shown in Table 1 to accomplish the task of searching, retrieving, and suggesting the

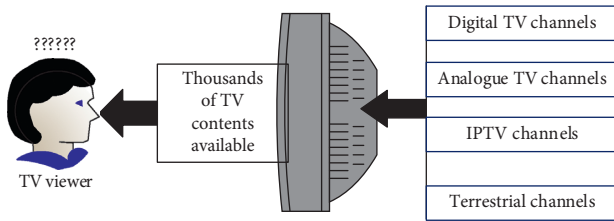


FIGURE 1: TV viewers often get confused with modern TV technologies.

right TV programs (items) for viewers through different recommender systems. Contextual information such as location, time, and physical conditions has also been applied in different recommendation scenarios [12].

Unfortunately, although the burden of information overload related to program consumption by TV viewers has been tackled to some extent, most of these existing personalized TV systems (e.g., [8–11]) did not exploit real-time social features/properties and personality traits of TV viewers to predict TV program interests/preferences. The incorporation of social (tie strength) and personality (traits) factors can help reduce the challenges of data sparsity (users rating a small proportion of items out of a larger number of available items) [13] and cold-start problems (new user and new item problems) [14] in TV recommender systems in order to significantly improve recommendation accuracy and quality of TV programs for viewers.

Consequently, this paper employs two main concepts, namely, personality and social properties/characteristics of TV users to generate effective and reliable group recommendations relating to TV program content. Social properties such as tie strength, closeness centrality, and degree centrality have been proved in literature [15–21] as very effective and important entities in social recommender systems. For instance, social ties and network centrality measures between attendees of a smart conference have positively been utilized to generate recommendations regarding conference attendees [15, 16], scholarly research papers [17, 18], and conference session venues [19–22].

Furthermore, some researchers who have worked on cold-start challenges in recommender systems [14, 23, 24] employed a wide variety of user profiles to generate recommendations without considering the personality of both new and existing users in different domains. Research has shown that personality is a stable and measurable psychological construct which can be used to explain various human behaviours using some traits [25]. This means that the concept of personality is capable of providing rich information. Moreover, Hu and Pu [26] proved that personality is the main and persistent factor which reflects the interests of people and predicts their behaviors. For example, the utilization of personality profiles can both provide recommendations for decision support and effectively solve cold-start issues [15, 16]. Therefore, it is appropriate to adopt new users' personality as their profiles [15, 16, 25, 26] to carry out a deeper study on TV program recommendations for viewers.

In order to decipher the enumerated research problem above, we propose a recommender algorithm called

Recommendation of Programs via Personality and Social Awareness (*ROPPSA*) for TV viewers. Specifically, *ROPPSA* utilizes normalization and folksonomy procedures to generate recommendations for TV viewers in groups that have strong similarities in terms of personality traits and tie strength with a Target TV Viewer (*TTV*). *ROPPSA* considers different sources of information including (i) personal (TV program interests of viewers), (ii) social (tie strengths between a *TTV* and TV viewers), and (iii) user personality traits between a *TTV* and TV viewers.

1.1. Contributions. The main contributions in this work are summarized as follows:

- (i) In our proposed recommendation method, we consider the social properties and personality traits of users by computing tie strengths and personality similarities between a *TTV* and TV viewers.
- (ii) Our recommendation method uses personality rating similarities coupled with a normalization procedure to generate reliable groups for personality group recommendations. Furthermore, our recommendation method utilizes the idea of tie strength computations and folksonomies to generate reliable groups for social group recommendations.
- (iii) The recommendation methodology developed in this paper reduces cold-start and data sparsity and is favourable for improving the social and personality awareness of smart and mobile TV viewers.
- (iv) Our proposed algorithm enables effective and reliable group recommendations of TV programs to TV viewers who have high tie strength and similar personalities with a *TTV* based on TV program interests.
- (v) Finally, our *ROPPSA* recommendation approach is evaluated and validated through an experimentation procedure, which utilized a relevant dataset for an experimental comparison with other contemporary recommendation techniques methods.

1.2. Structure of the Paper. The rest of this paper is organized as follows. Section 2 discusses related work. Section 3 describes our proposed *ROPPSA* recommender algorithm and model. Section 4 presents our experimentation procedure and results to show the effectiveness of our proposed *ROPPSA* method. Finally, Section 5 concludes this paper.

2. Related Studies

This section presents associated studies and literature relating to our study. We focus on related work pertaining to (i) personalized TV program recommender systems, (ii) social group TV recommender systems, and (iii) personality group recommender systems.

TABLE 1: Categories of traditional recommender systems.

Recommender system	Brief description
CBF	The CBF procedure involves the utilization of related content information with items and users. In CBF, recommendation of new items to a user involves matching content with items known to be of interest to the user [7]
CF	Using a rating process, the CF method is based on the notion that a user would usually be interested in items preferred by other users with similar interests [7]
HF	HF merges CF and CBF as well as other recommender algorithms/systems to reduce challenges such as data sparsity and cold-start [7]

2.1. Personalized TV Recommender Systems. Globally, a lot of researchers have made considerable efforts to develop effective personalized TV program recommender systems. A brief report of such related studies is presented as follows.

Krstic and Bjelica [27] designed a personalized TV program guide that employs a one-class classifier tool with an autoencoder neural network. Similarly, Martinez et al. [9] proposed a personalized TV program recommender system called *queveo.tv*, which hybridizes collaborative filtering and content filtering.

Furthermore, Kim et al. [1] generated personalized TV program recommendations for a target user by utilizing CF to propose a TV program recommender algorithm. Through genre and similar channel preferences, a rank model was employed to generate TV program recommendations in [1]. Similar to [1], Pyo et al. [2] used sequential pattern mining such as viewing time and watching length of each TV program to develop an automatic recommender algorithm for personalized TV program scheduling.

Kwon and Hong [28] employed memory-based CF to propose a personalized program recommender algorithm for smart TVs. The proposed method in [28] improved recommendation performance of EPGs and smart TV recommender applications. Similar to [28], Song et al. [6] presented a novel solution for content recommendation through the customization of IPTV content in accordance with current user context and environment, thereby ensuring better user experience.

The fundamental concept of group recommendation tries to maximize the group satisfaction function, which is generally based on periodically repeating recommendations or a partial satisfaction function after the sequence of items [29]. Kim et al. [30] proposed a TV program recommendation method by merging multiple preferences. They used channels and genres of programs as features for their recommendation method. Similarly, Chaudhry et al. [31] considered a heterogeneous information network environment and proposed to extract the heterogeneous relationship information between the target viewer and different TV programs following different metapaths, to deliver good quality recommendation using the implicit feedback history data of the viewer.

2.2. Social Group TV Recommender Systems. Social TV is defined as a social media service whereby TV users share familiarities about TV programs in a social network that they are viewing [3, 32]. Effective social TV service is typically

provided by considering two technicalities: (i) how to create social TV communities by grouping similar TV users? and (ii) how to recommend TV programs based on group and personal interests for personalizing TV? [3].

As a consequence of the above, Pyo et al. [3] employed two Latent Dirichlet Allocations (LDAs) and proposed a unified topic model, which recommends TV programs as a social TV service based on grouping similar TV users. Similar to [3], Wang et al. [33] established a group preference model by evaluating the external followers' impact on group interest using external experts' guidance for social TV group recommendation. Similar to [3, 33], Shin and Woo [34] proposed a socially aware TV program recommender for several viewers based on individual and group interests. In order to achieve this task, the authors merged user profiles by combining their common interests to generate social TV recommendations.

Shepstone et al. [35] presented a recommendation method which describes how audio analysis of age and gender in a group of TV viewers can be used to generate recommendations of TV programs for the group. Similarly, based on TV content and semantic reasoning techniques, Sotelo et al. [36] presented a method of TV program recommendation for groups of people.

2.3. Personality Group Recommender Systems. As a result of the fact that most methods model real-life conditions in group recommendation, the need for personality detection in a group is tremendously important [29]. In relation to personality inclusion in recommender systems, various types have been extensively proposed in [37–42].

In terms of personality group recommendations, Quijano-Sachnez et al. [43] described some new concepts of enhancing recommendations to people in different groups. Their approach maximized global group satisfaction by considering social associations and personality among each group. Similarly, Quijano-Sachnez et al. [44] ensured agreements within a group by defining alliances through personality and trust.

Similar to [43, 44], Quijano-Sachnez et al. [45] utilized three imperative features: past memory, trust, and personality to generate group recommendations. Similar to [45], Quijano-Sachnez et al. [46] proposed an entrusting-based recommendation method, which includes an analysis of personality in conflict situations and group characteristics such as size, structure, and trust between group members.

Recio-Garcia et al. [47] presented an innovative method of generating recommendations to groups based on CF and group personality composition. Similarly, through the utilization of personality and trust, Recio-Garcia et al. [48] proposed a Decision Support System for groups of people, where each user entrusts an agent that represents his/her interests. In order to generate personality group recommendations, Prada et al. [49] introduced diversity in the behaviour of social agents through a computational model of personality based on the Five-Factor Model (FFM).

In comparison with the existing TV program recommendation methods described above, our proposed *ROPPSA* method exhibits novelty and advantage of integrating social and personality awareness through the respective computations of tie strengths and personality similarities of TV users (*TTV* and other TV viewers) in order to establish strong ties and highly similar personalities between them for effective TV program recommendations.

Our method paves the way for TV users with strong ties (social relationships) and similar personalities to be grouped so that similar TV viewer groups are recommended similar TV programs as a result of their relationships and correspondences with one another. Consequently, personalized TV program recommendations are possible with the similar TV user groups related to social and personality awareness.

The fundamental recommendation process of *ROPPSA* is illustrated in Figure 2. Figure 2 involves TV viewers, various recommendation entities, and personality and social group recommendations of TV programs. The integration of individual user profiles represents a possible solution for recommending TV programs to multiple viewers. This process is referred to as group modeling or group recommendation [31].

To the best of our knowledge and with reference to the literature above, this is the first time tie strength and personality traits are being utilized to generate group recommendations for TV viewers.

In the next section, we present details on the design of our proposed *ROPPSA* recommendation method for TV viewers/users. Specifically, personality traits for TV recommendation are not available in the literature. This reason further corroborates our innovative objectives for proposing *ROPPSA* as a recommendation method for TV viewers in our society.

3. Algorithmic Design of *ROPPSA*

In this section, we present the fundamental concept and architecture of *ROPPSA*. Figure 3 illustrates that our *ROPPSA* recommendation model generates both social group and personality group TV program recommendations through initial computations of tie strengths and personality similarities among mobile TV viewers, respectively.

Referring to Figure 3, the *TV Viewer Crawler (TVC)* collects and sends personality trait ratings of individual TV viewers to the *Group Profile Organizer (GPO)*. The *GPO* is responsible for creating group profiles in accordance with personality trait ratings and interests of participants using a normalization procedure. The *Similarity Profiler (SP)*

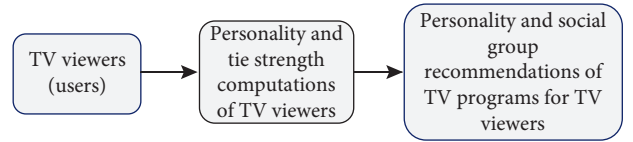


FIGURE 2: Fundamental recommendation procedure of *ROPPSA*.

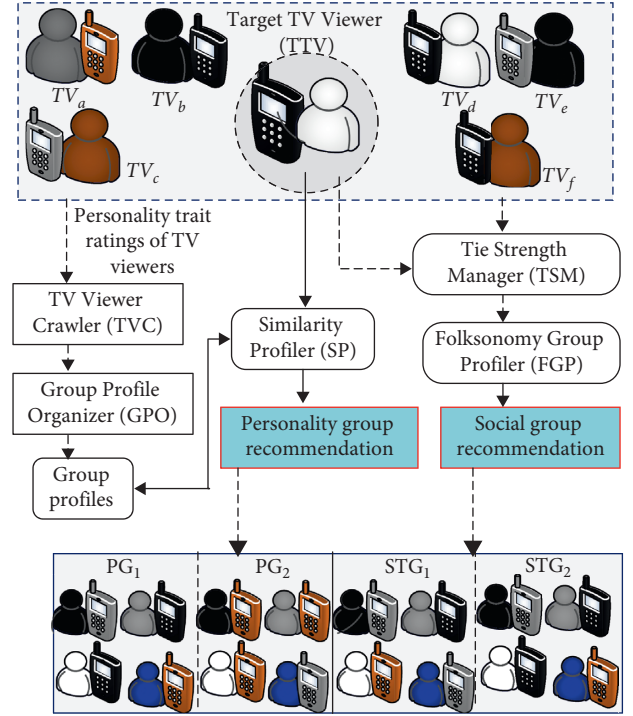


FIGURE 3: *ROPPSA* recommendation model.

computes similarities of personality trait ratings between the Target TV Viewer (*TTV*) and the created personality group profiles (pgp_b) in order to generate reliable and efficient personality group recommendations of TV programs based on the interests of the *TTV*.

The *Tie Strength Manager (TSM)* computes the contact frequencies and durations between the *TTV* and other TV viewers so that in accordance with their tie strengths, the *Folksonomy Group Profiler (FGP)* allocates groups for wider coverages of reliable and efficient social group recommendations based on program interests of the *TTV*.

The program interests of smart and mobile TV viewers can vary at any time as a result of modifications in TV schedules of a particular broadcasting station. Due to such variations, the recommendation process in *ROPPSA* depends on both mobile and smart TV viewer profiles in the current viewer situation. Due to the fact that *ROPPSA* operates on smart and mobile TVs, *ROPPSA* requires standard mobile and smart TVs with integrated operating systems, Internet, and web 2.0 features which use a web browser as a client supported by a programming language. We elaborate further on our *ROPPSA* recommendation framework below.

3.1. Capturing TV Program Preferences in ROPPSA. As stated earlier, in order to determine TV program preferences of TV viewers, *ROPPSA* initially utilizes and computes similar personalities between a *TTV* and other (grouped) TV viewers for its personality group recommendation service. Consequently, *ROPPSA* employs an explicit approach that allows TV viewers to input specific personality trait ratings from 1 to 5 using the Big Five Personality Traits (*BFPT*) [25]. *BFPT* consists of the following:

- (i) *Extraversion*: talkative, outgoing, energetic assertive, etc.
- (ii) *Agreeableness*: trusting, sympathetic, forgiving, generous, kind, appreciative, etc.
- (iii) *Openness*: wide interests, innovative insightful, imaginative, curious, artistic, etc.
- (iv) *Conscientiousness*: responsible, thorough, reliable, playful, organized, efficient, etc.
- (v) *Neuroticism (emotional stability)*: worrying, unstable, touchy, tense, self-pitying, anxious, etc.

ROPPSA further employs and computes tie strengths between a *TTV* and other (grouped) TV viewers (using their contact durations and frequencies) for its social group recommendation service.

3.2. Personality Group Profiling. Recommendation to groups usually involves the application of precise and appropriate characteristics in order to develop a compromise for different group semantics that validate disagreements and agreements among users [31, 44]. We organize our personality group profiling process illustrated in Figure 4 by adopting the arrangement of group recommendation in CF presented by Bobadilla et al. [7] and Asabere et al. [17]. Figure 4 demonstrates how our recommendation method combines TV viewer data and obtains data involving groups of TV viewers in four different steps.

The personality profiles of users (TV viewers) define their interests in terms of TV programs. Consequently, group profiles define common features used by individual TV viewers. We conformed to group profiling of individual TV viewers, by adopting the socially aware TV program recommender method used in [34]. As a consequence, we initially combine TV viewer profiles based on their personality trait ratings. The personality trait ratings of TV viewers are further arranged into groups by the *GPO* due to the fact that they have different traits and ratings.

As shown in Figure 4, the rating matrix of personality trait ratings by TV viewers is verified by TV_c in step 1. In steps 2 and 3, *GPO* generates neighbourhood intersections and group prediction phase (normalization), based on similar personality traits rated by TV viewers using (1). In the last step, *SP* decides which TV programs to recommend and generates a personality group recommendation based on the personality similarity between a *TTV* and the created personality group profiles (pgp_b).

Consequently, it is imperative to compute the weighted average associated with each personality trait rating using

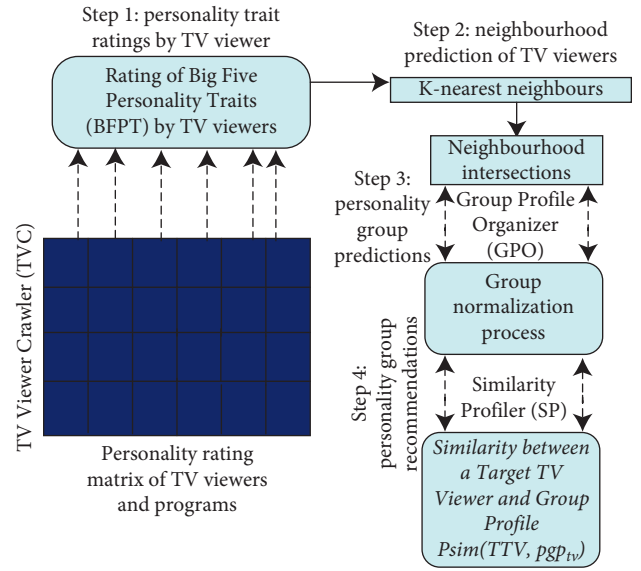


FIGURE 4: Personality group profiling and organization of TV viewers.

(2). This computation describes the program preferences of the TV viewers in order for the *GPO* to create a preference model for generating each group profile. As shown in Figure 4, *GPO* utilizes the *K-nearest neighbour* methodology by identifying unique personality trait ratings of TV viewers and categorizing them as a group [17, 31, 34]. Therefore, TV viewers with similar personality trait ratings are classified as nearest neighbours and grouped together.

Personality trait ratings of TV viewers are done on a scale of 1–5, where 1 and 5 are the lowest and the highest preference ratings, respectively. Let the TV program preferences of each group profile be $PGP = \{pgp_1, pgp_2, pgp_3, \dots, pgp_b\}$. The normalization process by *GPO* interconnects common neighbours and predicts different groups of TV viewers [17, 18]:

$$\text{norm_}TV_{a,b} = TV_{\min} + \frac{(TV_{\max} - TV_{\min}) \times TV_b}{PR_{\max} - PR_{\min}}. \quad (1)$$

We employ (1) to compute the normalized (n) values of personality trait ratings which have been rated differently by different TV viewers. In (1), $TV_{a,b}$ denotes individual personality trait ratings of the TV viewers, for a particular personality trait, where a is the notation for a particular TV viewer and b is his/her rating for a particular personality trait. The precise maximum and minimum ratings of the TV viewers for a particular personality trait are, respectively, represented as TV_{\max} and TV_{\min} . In addition, PR_{\max} and PR_{\min} represent the overall highest and lowest personality trait ratings in the experimental dataset. It must be emphasized that, in (1), PR_{\max} and PR_{\min} are, respectively, equal to 5 and 1, representing the highest and lowest possible personality trait ratings in the dataset [17, 18]:

$$pgp_b = \frac{\sum_{a=1}^{TV} \text{norm_}TV_{a,b}}{NTV}. \quad (2)$$

In (2), the values attained from (1) are totaled and divided by the number of TV viewers (NTV) who allotted ratings to a particular personality trait. Consequently, through (2), we compute and attain an average normalized value which designates the creation and allocation of a group profile for particular TV viewers. The TV viewers are allocated into their respective group profiles if their rating for a particular personality trait is greater than or equal to the corresponding average normalized value (pgp_b) of their group [17, 18].

With reference to Table 2, we demonstrate an example of our group profiling and normalization technique. In Table 2, there are four TV viewers with different personality trait ratings. For instance, in order to generate a group profile for the personality trait ‘‘Openness,’’ the first step of our proposed recommender algorithm is to count the number of available ratings related to ‘‘Openness.’’ Table 2 shows that there are four different ratings associated with ‘‘Openness’’ rated by each of the four TV viewers.

The normalized value of TV_a 's annotation on ‘‘Openness’’ with a rating of 3 is computed as follows:

$$\text{norm_}TV_{a,3} = 2 + \frac{(4-2) \times 3}{5-1} = 2 + \frac{6}{4} = 3.5. \quad (3)$$

Similarly, the normalized value of TV_b 's annotation on ‘‘Openness’’ with a rating of 2 is computed as follows:

$$\text{norm_}TV_{b,2} = 2 + \frac{(4-2) \times 2}{5-1} = 2 + \frac{4}{4} = 3. \quad (4)$$

Furthermore, the normalized value of TV_c 's annotation on Openness to experience with a rating of 4 is computed as follows:

$$\text{norm_}TV_{c,4} = 2 + \frac{(4-2) \times 4}{5-1} = 2 + \frac{8}{4} = 4. \quad (5)$$

Additionally, the normalized value of TV_d 's annotation on Openness to experience with a rating of 2 is computed as follows:

$$\text{norm_}TV_{d,2} = 2 + \frac{(4-2) \times 2}{5-1} = 2 + \frac{4}{4} = 3. \quad (6)$$

Consequently, the creation of a personality group profile (pgp_b) for the personality trait ‘‘Openness’’ in Table 2 is computed as follows:

$$pgp_b = \frac{\sum_{a=1}^{TV} \text{norm_}TV_{a,b}}{NTV} = \frac{3.5 + 3 + 4 + 3}{4} = 3.4. \quad (7)$$

The above normalization and personality group profiling approach in our proposed *ROPPSA* recommendation model illustrates that allocation of TV viewers to a personality group profile associated with ‘‘Openness’’ ratings should be assigned to TV viewers with ratings of 3.4 or above. This implies that, as per the data on Table 2, only two TV viewers, namely, TV_a and TV_c , can be assigned to that particular personality group profile for personality group recommendation of TV programs.

We employ equation (8) to determine the Personality Similarity ($PSim$) Score between TTV and pgp_b , i.e., $PSim(TTV, pgp_b)$. In (3), TTV and pgp_b are represented by a and b ,

TABLE 2: Normalization and personality group profiling process.

TV viewers	Personality traits	Ratings (1–5)
TV_a	Extroversion	5
	Agreeableness	3
	Openness	3
	Conscientiousness	2
	Neuroticism	2
TV_b	Extroversion	2
	Agreeableness	2
	Openness	2
	Conscientiousness	3
	Neuroticism	5
TV_c	Extroversion	3
	Agreeableness	2
	Openness	4
	Conscientiousness	1
	Neuroticism	1
TV_d	Extroversion	5
	Agreeableness	4
	Openness	2
	Conscientiousness	2
	Neuroticism	1

respectively. The average of all personality trait ratings of a and b is symbolized by \bar{P}_a and \bar{P}_b , respectively. Additionally, the personality trait ratings of a and b with one of the personality traits x are denoted by $P_{a,x}$ and $P_{b,x}$ respectively [15, 16, 26]:

$$PSim(a, b) = \frac{\sum_{x \in X} (P_{a,x} - \bar{P}_a)(P_{b,x} - \bar{P}_b)}{\sqrt{\sum_{x \in X} (P_{a,x} - \bar{P}_a)^2} \sqrt{\sum_{x \in X} (P_{b,x} - \bar{P}_b)^2}} \quad (8)$$

Our algorithm utilizes and returns a $PSim$ Score between -1 and 1 , where 1 indicates that TTV and pgp_{tv} have precisely the same or quite similar ratings and -1 denotes otherwise [15, 16, 26]. As a result of the fact that our recommender algorithm generates multiple personality group profiles for recommendation of TV programs, it loops through different TTV and pgp_b transactions in accordance with the dataset using (8). Furthermore, with reference to the range for $PSim$ Scores during experimentation, we set a threshold α in (9) for $PSim$ computations between TTV and pgp_b as follows:

$$PSim(TTV, pgp_b) \geq \alpha. \quad (9)$$

3.3. Tie Strength. In a social network, tie strength is defined as the extent to which users are close to each other in terms of social/collaborative relations. A high tie strength normally depicts strong social relations such as friendship and familiarities among users in a social network. Users in a social network with low tie strengths have weaker relationships in terms of closeness. In order to acquire essential and important information from users in a social network, the concept of ties represents a major channel for collaboration and communication. Ties establish communication links in a social network, thereby improving and providing key

elements for social cooperation and collaboration among users [15–21].

The concept of social ties/tie strength has been applied in different socially aware recommender algorithms and techniques [15–21]. Available evidence in the literature shows that these algorithms have performed considerably well in the alleviation of issues regarding cold-start and data sparsity as well as improved social recommendation accuracy [15–21]. Using the following equation, we measure and evaluate the tie strength between TTV and another TV viewer, TV_a

$$\text{Tie_Strength}_{TTV,TV_a}(t) = \frac{f_{TTV,TV_a} \times d_{TTV,TV_a}}{T}. \quad (10)$$

In (10), f_{TTV,TV_a} is the social contact frequency between TTV and TV_a in the time frame T and d_{TTV,TV_a} is their social contact duration within the same time frame T .

3.4. Social Group-Tie Profile Generation. The expansion of different social network communities substantiates innovative procedures and arrangements regarding the important role of self-organization principles. In the scope of this paper, we are interested in an algorithm which involves sharing of social resources, through the usage of a knowledge demonstration process called folksonomy [17, 50].

In order to generate social tie-group profiles in our *ROPPSA* recommendation model, we initially utilize the concept of folksonomies by connecting a TTV to other TV viewers in the dataset. In this paper, a folksonomy can further be described as a hypergraph $G = [TTV, TV, H]$, where TTV represents Target TV Viewers, TV represents other TV viewers, and $H = [h_1, h_2, h_3, \dots, h_n]$ denotes the set of hyperedges which only exist among the nodes (TV viewers) in different sets [17, 50].

With reference to Figure 5, a TTV is connected to different TV viewers through hyperedges h_1 and h_2 , respectively. TV viewers TV_a, TV_b, TV_c , and TV_d are connected to the TTV through hyperedge h_1 . Furthermore, TV viewers TV_e, TV_f, TV_g , and TV_h are connected to the TTV through hyperedge h_2 . We employ (10) to compute the tie strengths between TTV and all other TV viewers connected to hyperedges h_1 and h_2 . After computing the tie strengths, we utilize (11) to compute a threshold for the social tie-group profile ($stgp_{tv}$) which is connected through hyperedge h_3 :

$$stgp_{tv} = \frac{\text{sum of Tie_Strengths}}{\text{number of Tie_Strengths}}. \quad (11)$$

Using a time frame (T) of 660 minutes, we present an example of our social tie-group profile generation process in Table 3 and further explain how (10) and (11) are applied to generate social group recommendations for TV viewers.

Table 3 depicts the computation of tie strengths between TTV and other TV viewers using (10) which applies respective contact durations and frequencies. A close view of Table 3 depicts the tie strength for each computation of the TTV and other TV viewers. We employ (11) to compute the threshold of the social tie-group profile for the tie strength displayed in Table 3 as follows:

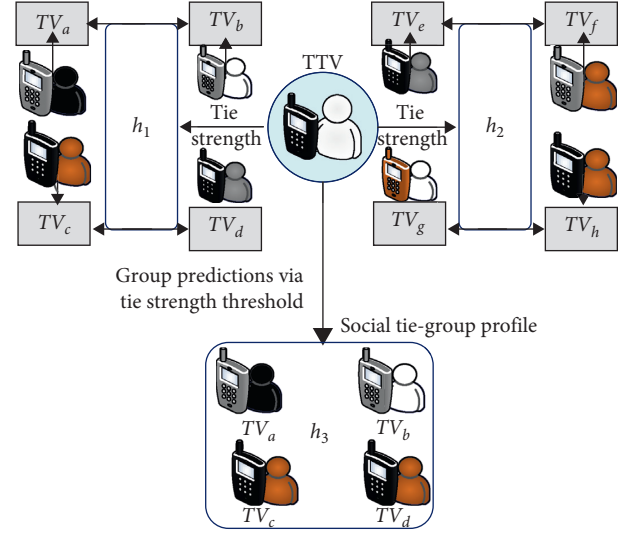


FIGURE 5: Social tie-group profiling and organization of TV viewers.

$$stgp_{tv} = \frac{0.6 + 0.6 + 0.3 + 0.1 + 0.2 + 0.2 + 0.3 + 0.2}{8} = \frac{2.3}{8} = 0.3. \quad (12)$$

The above social tie-group profiling approach in our proposed *ROPPSA* recommendation model demonstrates that the allocation of TV viewers to a social tie-group profile based on tie strength should be allotted to TV viewers who have a tie strength of 0.3 or above with a TTV . This implies that, as per the data on Table 3, only four TV viewers, namely, TV_a, TV_b, TV_c , and TV_g , can be assigned in that particular social tie-group profile to generate a social group recommendation of TV programs. This is depicted in the connections of hyperedge h_3 in Figure 5.

3.5. ROPPSA Recommender Algorithm. Our proposed *ROPPSA* recommender algorithm (Algorithm 1) displays the required inputs and outputs for personality and social group recommendation procedures. Variables in our recommender algorithm are declared in steps 2–4. In step 5, unique personality groups are identified. Steps 6–12 compute normalized personality groups using (1) and (2) and allocate TV viewers to their corresponding groups. Using (8), steps 13–16 compute the personality trait similarity between TTV 's and personality group profiles (pgp_b) in order to recommend TV programs to personality group profiles based on personality trait similarity threshold utilized through (9).

Similarly, steps 18–22 compute the tie strength between $TTVs$ and TV viewers using (10) and allocate TV viewers into social tie-group profiles using (11) as a threshold for social group recommendation of TV programs.

4. ROPPSA Experimentation Procedure

This section demonstrates our experimentation procedure for the evaluation of *ROPPSA*. Using an extended version of

TABLE 3: Social tie-group profiling process.

Target TV Viewer	TV viewers	Contact duration	Contact frequency	Tie strength
TTV	TV_a	5	7	0.6
	TV_b	3	6	0.6
	TV_c	3	5	0.3
	TV_d	2	4	0.1
	TV_e	2	3	0.2
	TV_f	2	4	0.2
	TV_g	2	6	0.3
	TV_h	2	5	0.2

the ATU dataset utilized in [21], we present our experimental results in comparison with other existing and relevant methods.

4.1. Experimental Dataset. In order to substantiate the procedure of our proposed recommender algorithm (ROPPSA), it was imperative that we utilize precise and relevant data for our experimentation process. Therefore, as stated above, we utilized and extended version of the Accra Technical University (ATU) dataset published in [21]. The ATU dataset in [21] needed to be extended because it did not contain personality trait ratings required for the experimentation in this paper. Consequently, we gathered more user, tie strength, and personality trait data from ATU students which we represented as TV viewers. Data were gathered from students in Higher National Diploma (HND) Marketing ($n=2864$), HND Computer Science ($n=720$), and HND Building Technology ($n=812$).

Therefore, the ATU dataset utilized in this paper contains a total of 4396 TV viewers (2421 males representing 55.07% and 1975 females representing 44.93%). Tie strength details of the ATU dataset utilized in this paper are illustrated in Figures 6 and 7.

The personality data gathered in our ATU dataset involved personality trait ratings by the ATU students (designated as TV viewers) in the dataset. Among the *BFPT*, students rated each personality traits using a scale of 1 to 5. The total number of personality ratings for all the traits combined in the ATU dataset is 22,541. Figure 8 illustrates the personality trait data utilized in our ATU dataset for experimentation.

Additionally, in order to ensure and substantiate recommendation accuracy in our experimentation procedure, we gathered TV program interests of TV viewers in accordance with the following: movie/TV series—*Horror, Action, Comedy, Adventure, and Drama*; sports/games—*Football, Basketball, Hockey, Boxing, and Athletics*. Tables 4 and 5 illustrate data regarding TV program interests of TV viewers in the ATU dataset in accordance with their ratings.

In relation to the ATU dataset, the total time frame (T) which is 1140 minutes utilized in [21] remained the same. Consequently, using (10), we computed $Tie_Strength_{TTV,TVa}(t) = (80 \times 7)/1440$ and achieved a result of 0.5 as the maximum (highest) Social Contact Score (SCS) between a *TTV* and other TV viewers for positive and effective social recommendations

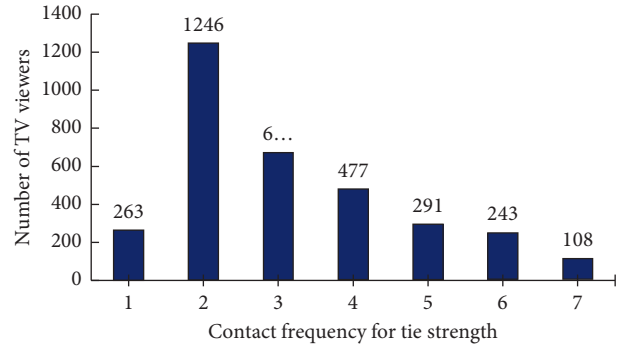


FIGURE 6: ATU dataset—contact frequency trends.

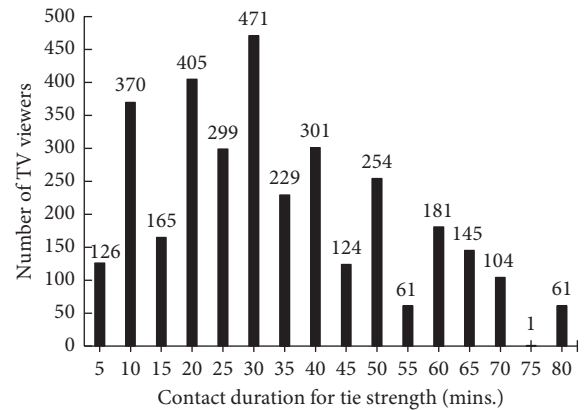


FIGURE 7: ATU dataset—contact duration trends.

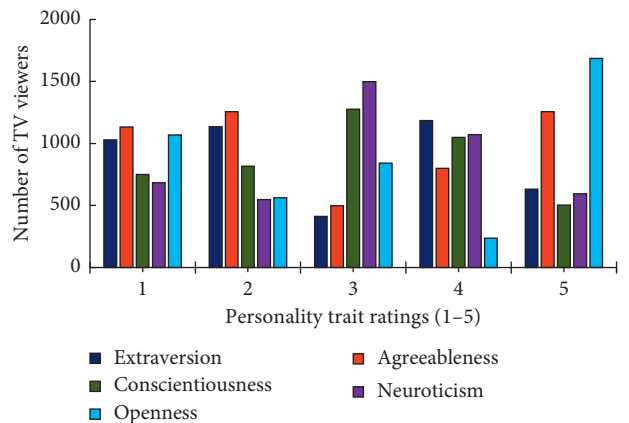


FIGURE 8: ATU dataset—personality data.


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Input:
Target TV Viewer ( $TTV$ )
TV viewers ( $TV_s$ )
Personality trait ratings of  $TTV$  and  $TV_s$ 
Tie strengths of  $TTV$  and  $TV_s$ 
Output:
 $TTV$  personality and social group recommendations for  $TV_s$ 
(1) procedure Personality and Social (Group) Recommendation of TV programs
(2) //Declare and Initialize Variables
(3)  $a$  and  $b$  //integer variables
(4)  $personality\_group\_threshold$ ,  $PSim\_threshold$  and  $tie\_strength\_group\_thresh$ ; //floating variables
(5) Identify unique personality trait ratings and classify as group
(6) //Compute normalized values of personality groups using (1) and (2)
(7) //Allocate TV viewers to respective groups
(8) for every TV viewer do
(9)   if (TV viewer[a].Rating  $\geq$   $personality\_group\_threshold$ ) then
(10)     Allocate TV viewer[a] in  $pgp[b]$ ;
(11)   end if
(12) end for
(13) //Compute PSim of  $TTV$  and  $pgp_b$  using (8) and (9)
(14)   if ( $PSsim(TTV, pgp_b) \geq PSim\_threshold$ ) then
(15)     recommend  $TTV$ 's TV programs to  $pgp_b$ ;
(16)   end if
(17) for every TV viewer do
(18)   Compute tie_strength between  $TTV$  and  $TV_s$  using (10) and (11)
(19)   if ( $Tie\_Strength(TTV, TV_s) \geq tie\_strength\_group\_thresh$ ) then
(20)     Allocate TV viewer[a] in  $stgp[b]$  and recommend
        $TTV$ 's TV programs to  $stgp_b$ ;
(21)   end if
(22) end for
(23) end procedure

```

ALGORITHM 1: ROPPSA pseudocode for personality and social group recommendations.

TABLE 4: ATU dataset—movie/TV series program ratings.

Category	Ratings (1–5)				
	1	2	3	4	5
Horror	1890	2139	85	170	112
Comedy	167	1941	2039	146	1941
Action	114	108	1951	148	2075
Adventure	120	1477	525	1702	572
Drama	164	1805	129	2007	291
Total ratings	2456	7472	4732	4177	4996

[15–21]. In ROPSAA, the quality of social group recommendations for TV viewers is determined through the corresponding level of tie strength computation a TTV has with a social tie group.

Through the utilization of (11) in accordance with the ATU dataset, more effective social group recommendations in terms of quality and accuracy were generated with SCSs between 0.3 and 0.5. Therefore, the priority TV program recommendation list for a particular social contact group was established based on computed recommendation values that fell within this threshold. However, SCSs which fell out of the above threshold were considered as unsuccessful TV program recommendations. Consequently, we experimentally established $0.1 \leq SCS \leq 0.5$ as the range for TV program

recommendation based on social contact (relations) and assigned a social group recommendation threshold of 0.3–0.5 in accordance with the dataset.

Typically, the computation of Rating Similarity Scores (RSSs) between two users/products is between -1 and 1 . A value of 0 indicates that there is no association between two users or variables [51]. Consequently, using (8), we experimentally established $0.6 \leq RSS \leq 1$ as the range for TV program recommendation based on personality traits and assigned a personality group recommendation threshold of $0.8-1$ using (9) according to the ATU dataset for successful recommendations in terms of prediction accuracy. Conversely, computed RSSs which fell out of the above threshold were considered as unsuccessful TV program recommendations.

4.2. Experimentation Setup and Evaluation Metrics. In our experimentation setup, we utilize a cross-validation technique to evaluate ROPPSA by initially partitioning our ATU dataset in training (80%) and test (20%) sets. The evaluation metrics employed in our experimentation of ROPPSA in the case of personality group recommendations focused on prediction accuracy. Therefore, we utilized root mean square error (RMSE), mean absolute error (MAE), and normalized mean absolute error (NMAE) in this regard. Lower values of

RMSE, MAE, and NMAE corroborate better performance. RSME is defined as follows [7]:

$$\text{RMSE} = \frac{\sqrt{\sum_{PR_{u,i} \in PR_{\text{test}}} (PR_{u,i} - \overline{PR_{u,i}})^2}}{|PR_{\text{test}}|}. \quad (13)$$

Additionally, MAE is defined as follows:

$$\text{MAE} = \frac{\sum_{PR_{u,i}} |PR_{u,i} - \overline{PR_{u,i}}|}{|PR_{\text{test}}|}, \quad (14)$$

where $|PR_{\text{test}}|$ denotes the number of personality trait ratings in the test set. $PR_{u,i}$ and $\overline{PR_{u,i}}$, respectively, represent the real and prediction values of the personality rating in $|PR_{\text{test}}|$. As a result of the fact that different recommender systems/algorithms may use different numerical scales, we employed NMAE in our experiments to ensure that experimental errors can be fully expressed on a normalized scale. We therefore used (15) to compute NMAE. In (15), PR_{max} and PR_{min} are denoted as the upper and lower limits of user personality trait ratings in our ATU dataset, respectively. Consequently, in accordance with our ATU dataset, $PR_{\text{max}} = 5$ and $PR_{\text{min}} = 1$ [7]:

$$\text{NMAE} = \frac{\text{MAE}}{PR_{\text{max}} - PR_{\text{min}}}. \quad (15)$$

In relation to social group recommendations, we focused on recommendation quality and therefore employed accuracy, recall, and f -measure ($F1$). Higher values of accuracy (A), recall (R), and $F1$ substantiate better performance. We employed (16) to compute the preciseness of a recommender algorithm by utilizing the accuracy metric as follows [7]:

$$A = \frac{\text{Num}(N, tv)}{\text{Num}(TV)}. \quad (16)$$

Additionally, we utilized the recall metric to measure coverage of all good and successful TV programs using the following equation [7]:

$$R = \frac{\text{Num}(N, tv)}{\text{Num}(tv)}. \quad (17)$$

In (16) and (17), $\text{Num}(N, tv)$ represents the number of relevant TV programs in the TV recommendation list for social group recommendation, $\text{Num}(TV)$ in (16) denotes the number of all TV program recommendations and $\text{Num}(tv)$ in (17) denotes TV programs that are relevant to a particular social group. Furthermore, in order to substantiate the results obtained through (16) and (17), we computed $F1$ using the following equation [7]:

$$F1 = \frac{2 \times A \times R}{A + R}. \quad (18)$$

4.2.1. Baseline Methods for Comparison. As a result of the fact that *ROPPSA* generates two main types of recommendations, namely, personality and social group recommendations, it was imperative to employ relevant methods for experimental comparison. Consequently, in order to validate our recommendation results in this paper, we

compare *ROPPSA* to the following relevant methods described below.

In relation to personality group recommendations for TV programs, we utilized the work done by Kim et al. [30] and Chaudhry et al. [31] and represented them as $T1$ and $T2$, respectively, for comparison in our experiments. Both $T1$ and $T2$ are relevant personalized group TV recommendation methods which involved similar approaches of combining/merging individual user profiles/models to select TV programs to suit groups of TV viewers.

Furthermore, in relation to social group recommendations for TV programs, we exploited the work presented by Shin and Woo [34] and Wang et al. [33]. We represented them as $T3$ and $T4$, respectively, for comparison in our experiments. Both $T3$ and $T4$ are relevant social group TV recommendation methods which involved similar approaches regarding the establishment of group preference profiles/models from individual TV viewer profiles which relate to common social similarity and interests in terms of TV programs. The main goal of our experimentation procedure was to verify the effectiveness of *ROPPSA* and improve recommendation accuracy by alleviating issues of data sparsity and cold-start in TV program recommendation. The experimental results below present evidence on how the above goals were achieved.

4.3. Experimental Results and Analysis. In order to evaluate the experimental results effectively, we validated our experimentation procedure by answering the following questions:

- (i) In comparison with $T1$, $T2$, $T3$, and $T4$, what was the overall assessment of *ROPPSA* in terms of TV program recommendation?
- (ii) During our experimentation procedure, was there a reduction of cold-start and data sparsity in *ROPPSA*, compared to $T1$ and $T2$ for personality TV program group recommendations and $T3$ and $T4$ for social TV program group recommendations?

In terms of personality group recommendations, we utilized RMSE, MAE, and NMAE to evaluate *ROPPSA* based on the computations and measurements of similar personalities between a TTV and groups of TV viewers as described above.

As shown in Figure 9, at the maximum Rating Similarity Score (RSS) of 1.0, *ROPPSA* attained the lowest MAE (0.763) in comparison with that of $T2$ (0.824) and $T1$ (0.937). Similarly, in Figure 10, at the maximum RSS of 1.0, *ROPPSA* achieved the lowest NMAE (0.190) in comparison with $T2$ (0.205) and $T1$ (0.234). Furthermore, the RMSE value of *ROPPSA* in Figure 11 is 0.759 at an RSS of 1.0, in comparison with $T2$ (0.820) and $T1$ (0.933). Subsequent results of MAE, MMAE, and RMSE in Figures 9–11 corroborate the effectiveness of *ROPPSA*.

Table 6 summarizes the performance comparisons of the above recommendation methods on the ATU dataset in terms of MAE and RMSE, respectively. The experimental results show that *ROPPSA* outperforms $T1$ and $T2$ in terms

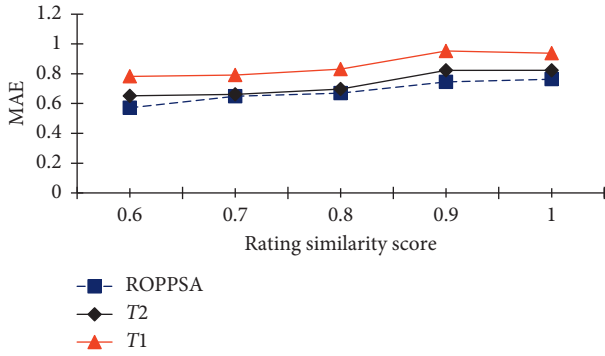


FIGURE 9: MAE performance on the ATU dataset.

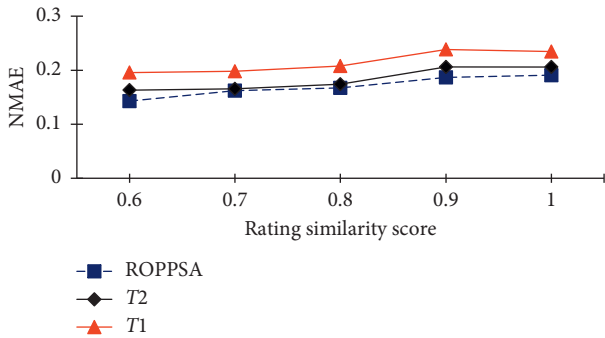


FIGURE 10: NMAE performance on the ATU dataset.

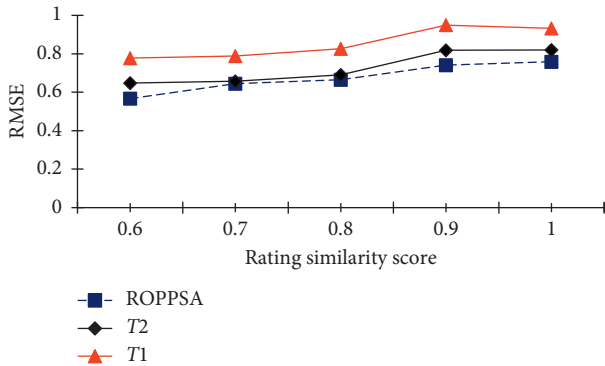


FIGURE 11: RSME performance on the ATU dataset.

TABLE 5: ATU dataset—sports TV program ratings.

Category	Ratings (1–5)				
	1	2	3	4	5
Football	1975	0	0	0	2421
Basketball	1381	594	2421	0	594
Hockey	2978	108	570	148	592
Boxing	1381	0	594	1483	938
Athletics	1381	2077	0	938	0
Total ratings	9097	2781	3588	2573	4550

of MAE and RMSE. This is because the use of personality trait information improves recommendation accuracy and performance by compelling TV viewers to be more similar in

terms of personality. It can also be observed that *T2* and *ROPPSA* outperform *T1* in terms of RMSE and MAE due to the same utilization of personality information. This further proves and substantiates the necessity and effectiveness of integrating personality information into TV program recommendation methods for performance improvement.

The experimental results in Table 6 and Figures 9–11 reveal that the use of personality as a TV program recommendation entity for TV viewers can help to further improve prediction accuracy by determining more similar group TV viewers because direct personality information expresses similarities between TV viewers’ program interests to some extent.

In our experimentation analysis, Figure 12 shows that at the maximum threshold value for social contact (0.5), *ROPPSA* achieved the highest accuracy value (0.237) when compared with *T3* (0.177) and *T4* (0.062). *ROPPSA* therefore generated more effective and successful TV program recommendations (high accuracy) than *T3* and *T4*.

Higher recall specifies that a recommender algorithm returned the most relevant and effective results (TV recommendations) and exhibited minimal false-negative errors. According to Figure 13, the recall values of *ROPPSA* are higher than those of *T3* and *T4*. Specifically, at the highest Social Contact Score of 0.5, *ROPPSA* achieved a higher recall (0.778) than *T3* (0.569) and *T4* (0.515). Therefore, *ROPPSA* outperformed *T3* and *T4* in terms of recall and hence generated more relevant and successful social group recommendation of TV programs (high recall).

In order to verify the transparency and authenticity of our experimental results for accuracy and recall in Figures 12 and 13, we computed *F1* using (18). A critical view of Figure 14 shows that *ROPPSA* attained higher results (0.363) in terms of *F1* in comparison with *T3* (0.269) and *T4* (0.112). This correspondence is due to the efficacy of information retrieval with respect to how *ROPPSA* devoted more importance to both accuracy and recall in terms of social group TV program recommendation. Furthermore, the positive transparency of *F1* in social group recommendations is due to the outperformance of *ROPPSA* in accuracy and recall evaluation metrics in comparison with *T3* and *T4*.

Additionally, in relation to the arithmetic mean (AM) results of accuracy and recall using (19), *ROPPSA* achieved higher results in comparison with *T3* and *T4*. As shown in Table 7 and Figure 15, in terms of social group recommendation, at the highest tie strength (0.5), we attained AM results of 0.507, 0.373, and 0.289 for *ROPPSA*, *T3*, and *T4*, respectively:

$$AM = \frac{1}{2} \times (A + R). \tag{19}$$

Our approach proves that the AM results attained for *ROPPSA* were the highest in comparison with the *F1* (harmonic mean) results, which accordingly corroborates that AM should always be higher than harmonic mean regarding the retrieval effectiveness of a recommender system/algorithm [52].

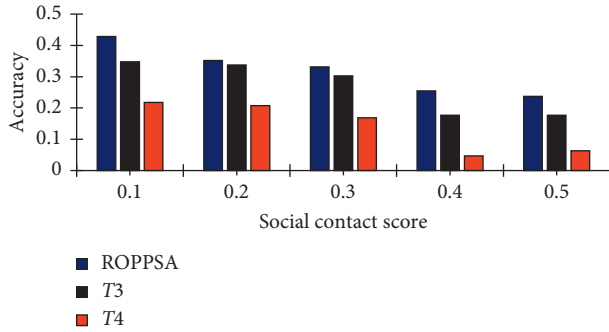


FIGURE 12: Performance evaluation for accuracy on the ATU dataset.

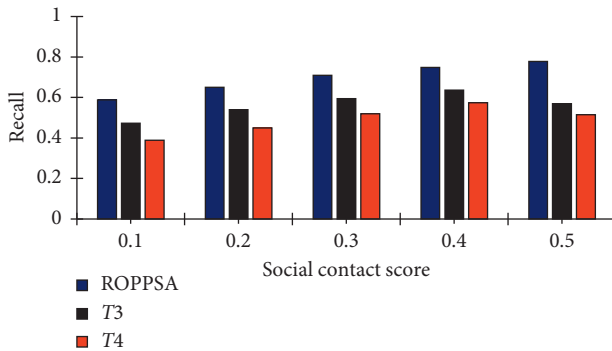


FIGURE 13: Performance evaluation for recall on the ATU dataset.

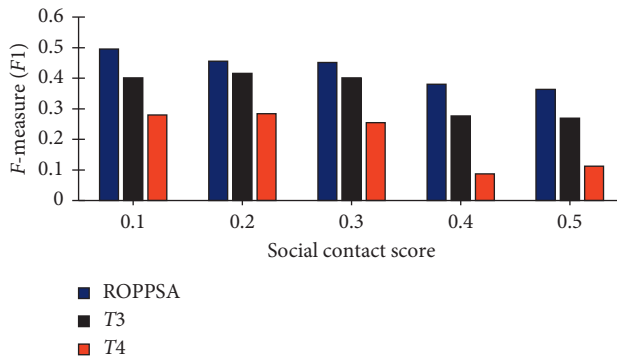


FIGURE 14: Performance evaluation for f -measure ($F1$) on the ATU dataset.

TABLE 6: RSME and MAE performance on the ATU dataset.

$PSim$	MAE performance			RMSE performance		
	T2	ROPPSA	T1	T2	ROPPSA	T1
0.8	0.696	0.669	0.830	0.690	0.665	0.826
0.9	0.823	0.745	0.953	0.819	0.741	0.949
1.0	0.824	0.763	0.937	0.820	0.759	0.933

4.4. Summary of Experimental Results. In summary, it can be verified from Figures 9–15, as well as Tables 6 and 7, that *ROPPSA* reliably attained more favourable results in all the utilized evaluation metrics. This observation indicates that our approach is more suitable and robust due to its capability

TABLE 7: Experimental comparison of AM and $F1$.

Method	Highest SCS	Accuracy	Recall	AM	$F1$
T3	0.5	0.177	0.569	0.373	0.269
ROPPSA	0.5	0.237	0.778	0.507	0.363
T4	0.5	0.062	0.515	0.289	0.112

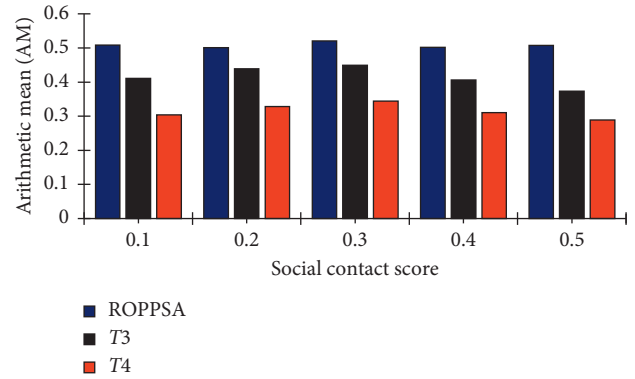


FIGURE 15: Performance evaluation for arithmetic mean (AM) on the ATU dataset.

to make use of tie strengths and personality trait ratings of TV viewers. Consequently, in comparison with the baseline methods, *ROPPSA* alleviated the challenges of cold-start and data sparsity due to the unlimited utilization of both personality and social features of TV viewers.

Our proposed *ROPPSA* recommender algorithm outperformed both $T1$ and $T2$ as well as $T3$ and $T4$ in terms of personality and social group recommendations, respectively. This exemplifies the importance of personality group profile normalization and social group relationships/influences in generating effective and efficient TV program recommendations for TV viewers.

5. Discussion and Concluding Remarks

With reference to our research findings and our proposed recommendation method (*ROPPSA*), it is extremely important and vital to note that, globally, the data protection law of every nation has an objective to protect individuals' fundamental rights to privacy and the protection of their personal data [53, 54]. Ghiglieri et al. [54] undertook an online survey which involved 200 participants to determine whether consumers were aware of smart TV-related privacy risks. The main findings in Ghiglieri et al. [54] depicted that generally participants are unwilling to disconnect the Internet from their smart TVs because they value the smart TV's Internet functionality more than their privacy [54].

In Germany, a sectoral investigation was upgraded into a concrete policy guidance for smart TV stakeholder/users in relation to privacy/data issues of television services in the nation's ecosystem. Additionally, the Netherlands has recently witnessed the implementation/enactment of three enforcement actions by the Dutch Data Protection Authority against leading providers of interactive television services [53]. These examples corroborate that the effective

implementation of our proposed *ROPPSA* method should be done in cognizance with the Data Protection Act/law of respective nations and such acts/laws should have content relating to privacy/personal data of smart TV stakeholder/users [53, 54].

Most existing TV program recommendation methods disregard the fact that people often exhibit similar personality traits and tie strengths in terms of different program interests or preferences. In this paper, we proposed an innovative recommendation method called *ROPPSA* for TV recommendation in social and personality groups. *ROPPSA* generates similar personalities and tie strengths among *TTVs* and TV viewers for improving group recommendation accuracy using two different procedures. We carried out an extensive experimentation procedure using a relevant ATU dataset. Experimental results show that our proposed *ROPPSA* method outperformed other relevant TV program recommendation methods in terms of recommendation accuracy and other utilized metrics.

In future, it is our aim to explore more social-based patterns pertaining to TV program recommendation by applying other social property features involving network centrality measures. Consequently, relevant TV viewers in such a method will be determined by analyzing their information pertaining to network centrality.

Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Supplementary Materials

The dataset utilized in this research article involves relevant data collected from students in Accra Technical University (ATU), Ghana, and is an extension from a dataset used in [1]. Data were gathered from students in Higher National Diploma (HND) Marketing ($n = 2864$), HND Computer Science ($n = 720$), and HND Building Technology ($n = 812$). Therefore, the ATU dataset utilized in this paper contains a total of 4,396 TV viewers (2,421 males representing 55.07% and 1,975 females representing 44.93%). The ATU dataset in this research article contains tie strength data which comprises computations of contact frequencies (Figure 1) and contact duration (Figure 2) of ATU students (users designated as TV viewers). The ATU dataset also comprises personality trait ratings (scale of 1 to 5) of all users (TV viewers) in accordance with the Big Five Personality Traits (BFPT). The total number of personality ratings for all the traits combined in the ATU dataset is 22,541. Figure 3 illustrates the personality trait data utilized in our ATU dataset for experimentation. Additionally, in order to ensure and substantiate recommendation accuracy in our experimentation procedure, we gathered TV program interest of TV viewers in accordance with the following: movie/TV series-horror, action, comedy, adventure, and drama; sports/

games-football, basketball, hockey, boxing, and athletics. Tables 1 and 2 illustrate data regarding TV program interest of TV viewers in the ATU dataset in accordance with their ratings. Figure 1: ATU dataset—contact frequency trends. Figure 2: ATU dataset—contact duration trends. Figure 3: ATU dataset1—personality data. Table 1: ATU dataset—sports TV program ratings. Table 2: ATU dataset—movie/TV series program ratings. (*Supplementary Materials*)

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