HyPeRM: A HYBRID PERSONALITY-AWARE RECOMMENDER FOR MOVIE

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ABSTRACT

Recommendation systems aim to provide end users with suggestions about items, social elements, products or services that are likely to be of their interests. Most studies on recommender systems focus on finding ways to improve the recommendations, including personalizing the systems based on details such as demographics, location, time and emotion, among others. In this work, a hybrid recommender system, namely HyPeRM, is presented, which uses users' personality traits along with their demographic details (i.e. age and gender) to improve the overall quality of recommendations. The popular Big Five personality trait measurement scale was used to gauge users' personalities. HyPeRM was evaluated using two metrics, that is, Standardized Root Mean Square Residual (SRMR) and Root Mean Square Error of Approximation (RMSEA). Both ~~the~~ metrics revealed that HyPeRM outperformed the baseline model (i.e. one without user's personality) in terms of the recommendation accuracies. The study shows that user recommendations can be further enhanced when their personality traits are taken into consideration, and thus their overall search experience can be improved as well.

Keywords: recommender system, personality, age, gender, content-based filtering, collaborative filtering

1.0 INTRODUCTION

Online shopping has seen a phenomenal boom with the advent of Internet, and thus there is a need to store a huge amount of information about users and shopping items, resulting in significant content explosion and information overload. The task of searching for an item or service can be simplified with the aid of a recommender system. A system that provides affordable, personal, and high-quality recommendations to the user. The system supports online users in decision-making, planning and purchasing processes [6]. A number of recommender systems have been developed to aid individual users in finding items of interest among the millions of items available, which include books [25, 31], movies [35, 33, 25, 2, 12], and music [36, 11, 37, 38], among others.

Recommender systems normally acquire data about user' activities and build user models to filter the preferences expressed either explicitly (typically ratings as in Amazon.com) or implicitly (monitoring user' behavior such as websites visited, songs heard and books read [21, 17]. The recommender technology is superior to other information filtering applications because of its ability to provide personalized and meaningful information recommendations. For example, while standard search engines are very likely to generate the same results to different users entering identical search queries, recommender systems are able to generate personalized results which are more relevant to the user as they take each user's personal interests into account [34].

As users of recommender systems may have different needs in various situations and contexts, it is becoming increasingly important to consider contextual data when filtering information [39]. This resulted in the birth of personalized recommendations, focusing on various user contexts such as time of access [40, 38, 42], location of access [40, 43, 41], emotion [37, 38], mood [33, 41] and more interestingly users' personality traits [27, 14, 41]. In fact, studies have shown significant connections between personality and people's tastes and interests. For example,

Cantador et al. [10] revealed similar personality traits between users who like action and comedy movies. Similarly, those who like romance films show strong personality resemblance to those who like comedies and dramas. Studies on personality-based recommender systems are showing promising results, however they are scarce.
Collaborative filtering (CF) and Content-Based (CB) filtering are the two main filtering techniques used in recommender systems. Each of these techniques has its own advantages and disadvantages; hence there is a trend in merging them to facilitate the improvement of their overall performance [35]. In fact, studies generally attempt to combine CF and CB with other approaches, such as demographic filtering (DF) or social filtering (SF). The DF approach involves the use of users' personal or demographic features such as age, gender, nationality and education levels, with the assumption that users with similar demographic attributes have similar interests [45, 26].

Drawing inspirations from the current trend in recommender systems, we propose HyPeRM (Hybrid Personality-aware Recommender for Movies), which aims to improve movie recommendations by taking users demographic and personality traits into account. The study is novel in the sense that it uses a hybrid filtering (i.e. CF-CB-DF), and further refines and filters users' preferences based on their personality traits. HyPeRM was evaluated and compared against the CF-CB-DF only system (i.e. baseline). As will be shown later, results indicate recommendation accuracies improved significantly when user's personality traits were taken into consideration.

The rest of this research article is structured as follows: section 2 presents some of the related studies, followed by the research design and methodology of this study. Section 4 provides the experimental results and discussions. The paper is finally concluded in section 5.

2.0 LITERATURE REVIEW

Recommender systems are gaining importance as the amount of available information and content is expanding rapidly, rendering it difficult for end users to find suitable content in large databases where most of the content is irrelevant. There are many types of recommendation algorithms characterized by their filtering techniques, but the two most popular algorithms are collaborating filtering (CF) and content-based filtering (CB).

CF is one of the most common and successful recommendation algorithms for personalized recommender systems. Basically, CF stores and analyzes the user behavior and tries to find the set of similar user behavior to generate recommendations. In other words, it recommends items that people with similar tastes and preferences liked in the past [32, 27]. Although CF method suffers from a cold start problem in which inadequate ratings were obtained for a new item, it has been successfully applied to real world problems, such as music [22], TV shows [14], movies [2, 12, 6] and tourism [15]. More popular examples are Amazon.com that recommends books based on user's purchasing behaviour, and also MovieLens, which recommends movies based on the preferences of people with similar tastes and interests.

On the other hand, content-based (CB) recommendation systems recommend items that are similar to the ones preferred by the user in the past [32]. Therefore, CB does not consider other users' ratings into account, and thus the recommendation can be considered to be unique to the user. Examples of studies on CB approaches include Bogdanov et al. [5] who developed a music recommender, and Mooney and Roy [53] who developed a book recommender by making personalized suggestions based on previous examples of users' likes and dislikes. Another example is Pandora Radio, a system that recommends music compositions similar to the one the user already likes. CB approaches can overcome the cold start problems [3], however the systems suffer from overspecialization, a scenario in which the user is recommended only the same types of the items he/she used to like in the past [23].

Users' demographic information has also been introduced to increase recommendation accuracies, with the assumption that users with similar demographic attributes have similar interests. The recommender obtains group of users having similar demographic attributes forming a neighborhood from which newly recommended items are generated [45]. Unlike CF and CB approaches, the demographic filtering approach (DF) does not require a history of user ratings. Studies in recommender systems using demographic data include systems for movies [25], and web pages [16], to name a few.

Hybrid filtering combining both CF and CB, or other recommendation strategies is gaining momentum. One of the earliest works that merged CF, CB and DF techniques was conducted by Pazzani [53] who developed a recommender system that predicts the best restaurant based on users' preferences, ratings and demographic features. Bollacker et al. [7] combined CF and CB in developing an automatic citation analysis system whereas Garden and Dudek [54] used semantics in the CB module and merged it together with CF to recommend movies. Another recent study by Pera and Ng [25] proposed GroupReM, a group recommender system for movies using both CF and CB, particularly based on content similarity and popularity. Chen and He [44] combined CF and DF approaches in order to recommend movies. The user's age, gender and occupation data were gathered, and users' similarities were determined based on previous results (CF). Their experiments showed the quality of recommendations to improve with the inclusion of users' demographic data.

Recently, studies have demonstrated the importance of psychological aspects of people such as their personality traits and emotions during the decision-making process [14]. Personality refers to the enduring patterns of thought, feeling, motivation and behavior that are expressed in different circumstances [20]. One of the most widely used model to determine users' personality is the Big Five, which is a hierarchical organization of personality traits in terms of five basic dimensions: extraversion (E), agreeableness (A), conscientiousness (C), neuroticism (N) and openness (O). The order of the factors is also considered important as the first two traits, that is, *E* and *A* account for the largest percentage of variance in personality [46]. Big Five is deemed to adequately represent the basic dimensions of user personality as its dimensions are stable, universal, cross-culturally applicable and have biological basis [20]. It is also one of the most widely used and recognized instrument in determining user's personality [19]

Tkalcic et al. [24] used Big Five to propose a personality-based approach for CF recommender system, in which three similarity measures were compared: ratings, Euclidian distance with Big Five data and weighted Euclidian distance with Big Five data. The authors found the recommendation to improve when the Big Five data were considered. In 2010, Nunes used fine-grained (30 facets and Big Five) and coarse-grained (only Big Five) questionnaires in order to assess the impact of personality traits on presidential voting [27]. The respondents were asked to describe three presidential candidates' personalities using the two sets of questionnaires, and the system recommends the candidate to be voted. The respondents then have to indicate if the system recommended the right candidate. The study revealed that when the five dimensions of the Big Five model were taken into account the accuracy of the recommendation was 80%, whereas it reached 100% when the dimensions were decomposed to 30 facets (i.e. fine-grained). The findings however, cannot be generalized as only 10% of their 100 respondents completed the questionnaires.

Another personality-based recommender system study was carried out by Hu and Pu [55], who based their system on the correlations between musical preferences and personality types. Users' personalities were determined using Big Five whereas the similarity between two users were estimated using the Pearson correlation coefficients (PCC). The study found the personality-based approach achieved a significant improvement over the baseline system, which only considers user ratings. A similar finding was reported recently by Braunhofer et al. [41], who proposed to improve recommendations of places of interests to tourists by learning users' preferences from their past ratings as well as their personality. The authors also used the Big Five questionnaire to elicit user's personality, which was then exploited to actively learn their preferences.

3.0 RESEARCH METHODOLOGY

In this section, we present our proposed recommender, HyPeRM, which generates personalized movie recommendations by integrating users' personality traits and their age and gender details. Fig. 1 depicts the overall HyPeRM model, which can be categorized into three main sections, namely registration, user profiling and recommendation.

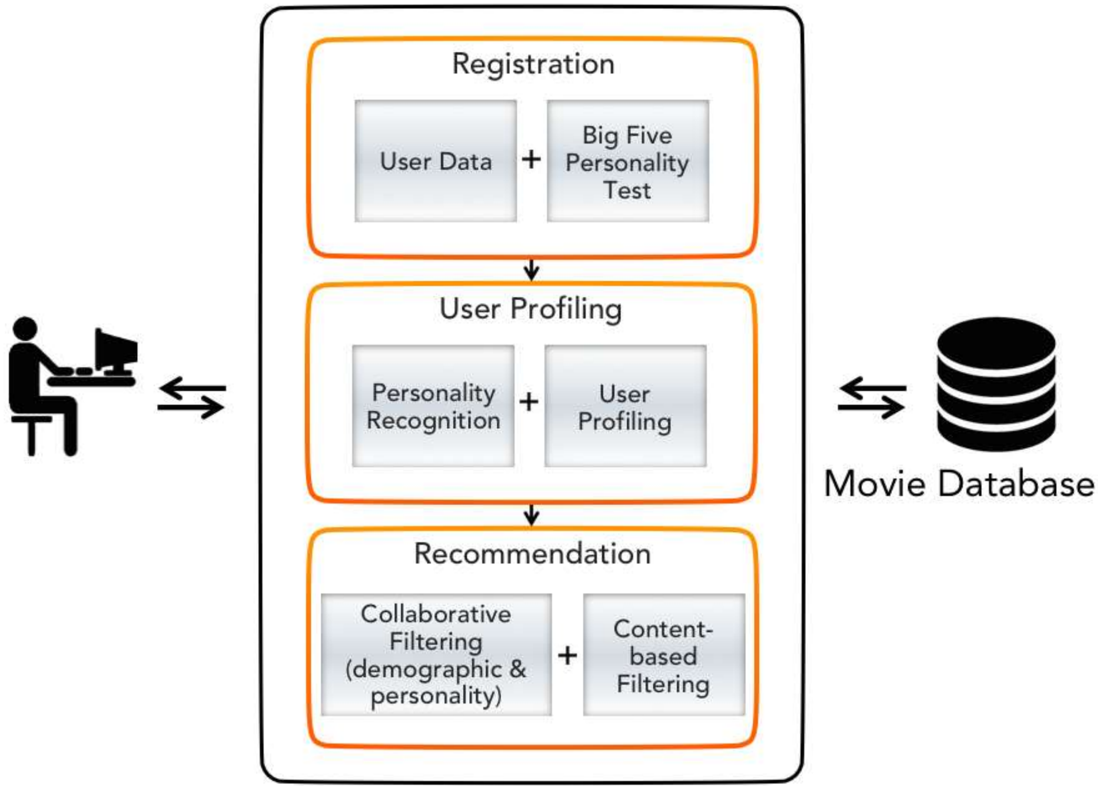

Fig. 1. The HyPeRM Model

The model can be briefly described as follows:

i. A user provides his/her basic demographic details, and answers the Big Five personality questionnaire (i.e. a one-time step). The questionnaire's goal is to create a brief inventory that would allow efficient and flexible assessment of the five dimensions when there is no need for more differentiated measurement of individual facets [47]. Kindly refer to Appendix A for the Big Five questionnaire.

ii. The system performs user profiling based on the demographic and personality data.

iii. The system first filters the potential results based on the user's age and gender (DF). This is then followed by personality filtering based on the Big Five results (i.e. Neuroticism, Conscientiousness, Extraversion, Agreeableness, or Openness).

iv. The system then applies CF to filter the movies based on other users with similar age, gender and/or personality. The rating history of similar users and the mean squared approach were applied for CF. Mean squared difference focuses on achieving a good level of accuracy on the recommendations. Higher frequency of user rating increases the accuracy of the recommendations for the user. The similarity between two users (*x* and *y*) can be estimated based on Eq. 1 below [30]:

$$sim(x,y) = \frac{1}{I}\sum_{i=1}^{I}\left(r_{x,y} - r_{y,i}\right)^2 \tag{1}$$

Based on the computation of mean squared difference, if say user *X* has rated five movies based on his/her preference, this user *X* will most probably have similar values with another user (user *Y*). However, with higher number of rating obtained, the recommendation accuracy increases or only users with minimum number of rated items are taken into consideration. In this case, the Mean Absolute Error [30] was calculated.

v. On the other hand, if the user is new to the system then CB filtering is applied, and thus the recommendations are made based on a keyword search. It filters the recommended movies based details such as genre and title, without considering the user's personality data. The movie details were downloaded from IMDB (http://www.imdb.com/interfaces), which is approximately 206MB in size. Ultimately, the system displays the recommended movies to the user.

The next section illustrates how HyPeRM was developed and tested.

3.1 HYPERM DEVELOPMENT AND IMPLEMENTATION

HyPeRM was developed in C#, with MS SQL Server 2008 R2 for the database implementation. It was designed based on twenty-one generic keywords covering genres such as horror, comedy, romantic, thriller and crime, among others. The following screen grabs illustrate the different scenarios for HyPeRM.

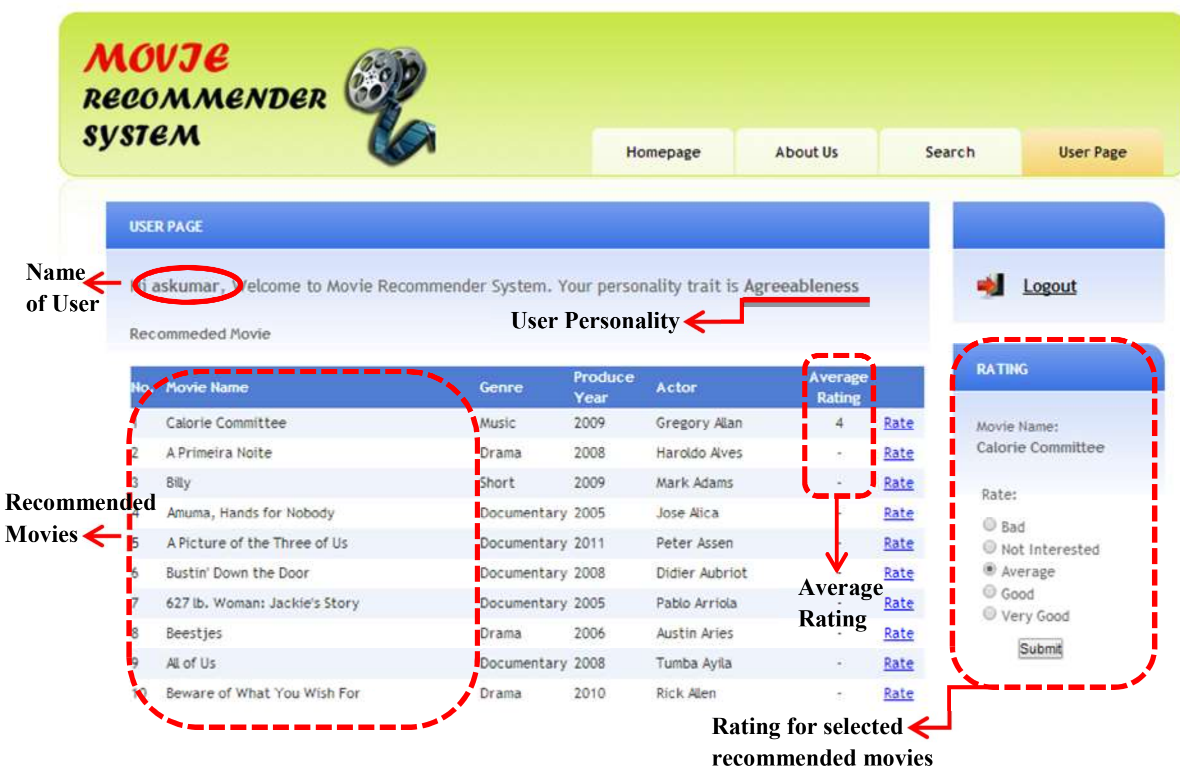

Fig. 2 Recommended movies for User 1

Fig. 2 shows a sample interface for User 1 upon registration (e.g. Male; age = 31 – 40 years old; personality = Agreeableness). A list of the initial recommended movies is displayed, along with the average ratings (if available). User 1 will be able to browse through the list of movies, and indicate his/her rating for specific movies. These ratings will be taken into consideration when User 1 returns to the system later, or when other users with similar traits perform a similar search.

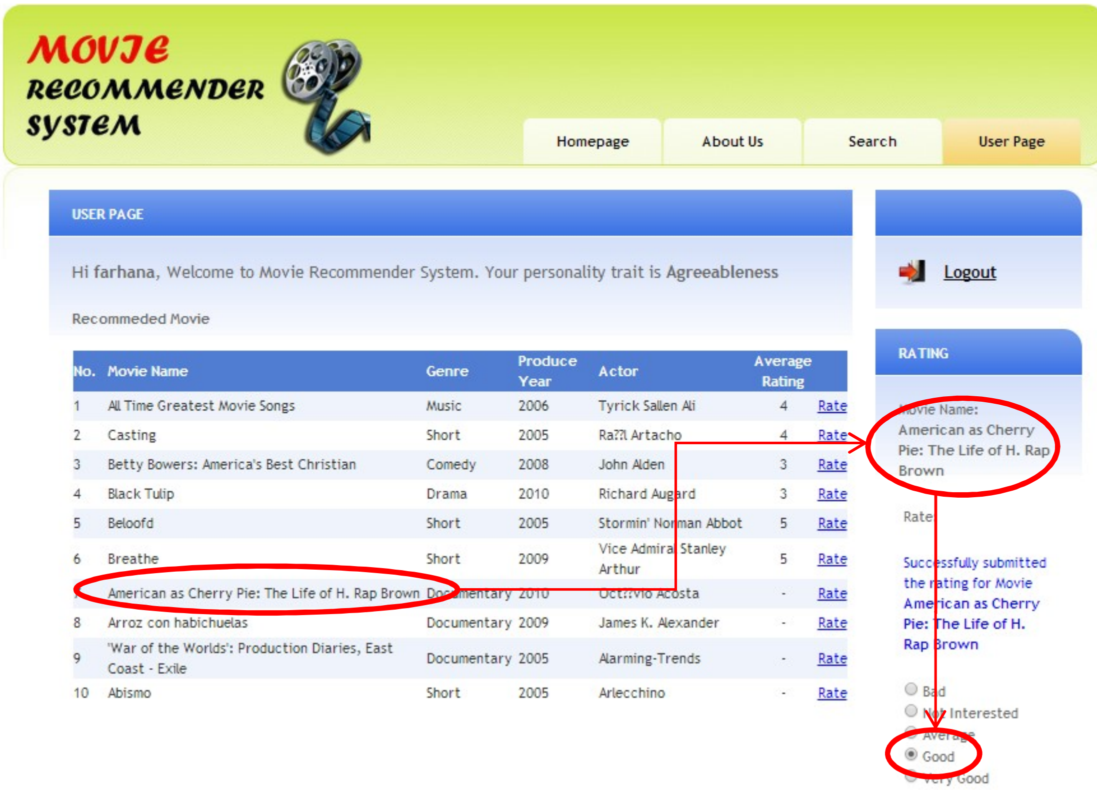

Fig. 3 Recommended movies for User 2

Fig. 3 illustrates User 2 with the same personality trait as User 1 (Agreeableness), but with different demographic details (i.e. Female; age = 21 - 30). HyPeRM presents a different list of recommended movies to User 2 compared to User 1 as the demographic information of these two users are not the same. Nevertheless, it can be noted that movies with similar genres are being recommended, probably due to the similar personality trait.

Assuming User 2 rates *American as Cherry Pie* (i.e. item #7) as good, HyPeRM then considers this rate when User 2 logs into the system again. As shown in Fig. 4 below, *American as Cherry Pie* is listed as item #2.

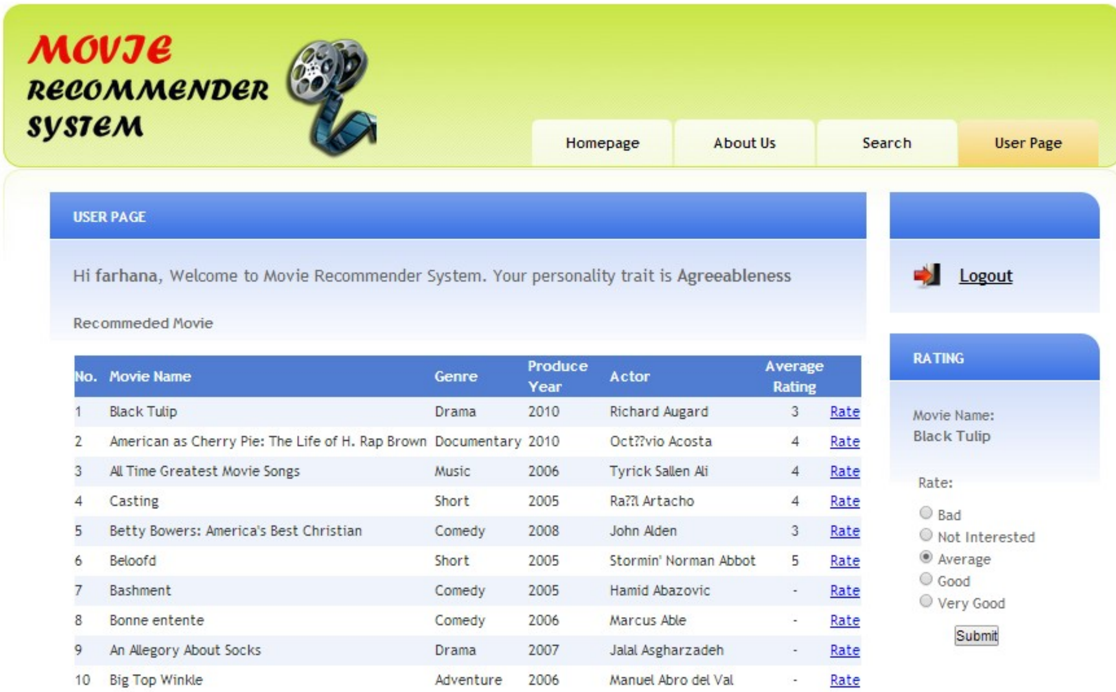

Fig 4 Recommended movies for User 2 on a subsequent login

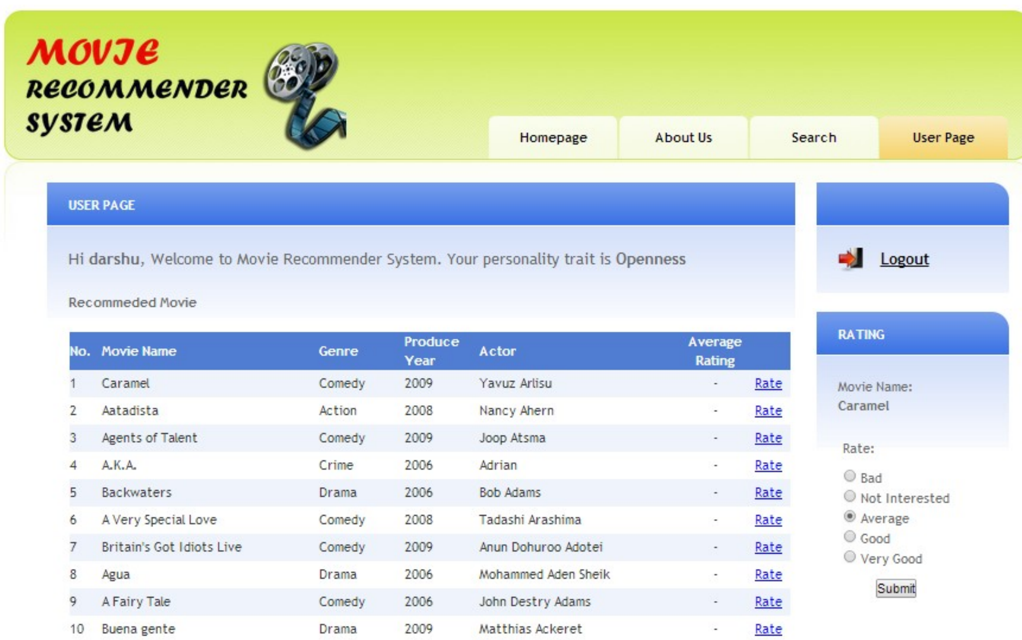

Fig. 5 Recommended movies for User 3

Finally, Fig. 5 depicts a scenario for User 3 with the same demographic profile as User 2 but with a different personality trait (i.e. Openness). Comparing the list of movies between the two users, it can be concluded that the recommendations are influenced more by the users' personalities, instead of their demographic details.

3.2 EXPERIMENTAL SETUP

The goals of the experimental evaluation are to verify the effectiveness of HyPeRM, and to assess the accuracy of the recommendation based on users' personality.

HyPeRM was tested by ten users (M_{age} = 31), all with good technical skill. The experiment was conducted in a lab, with the system developer providing a brief demonstration on how to use HyPeRM. The users were instructed to create their profiles first, and to answer the Big Five personality questionnaire. Upon completion, they were asked to use the system and perform searches for movies based on the genres. They were also encouraged to rate the movies to indicate if the recommended movie fits their interests or personality. The experiment lasted for 20 – 30 minutes. All the information from the users were captured in Microsoft SQL Server database.

3.3 EVALUATION METRICS

The accuracy of the recommendation was evaluated using two popular metrics, namely Standardized Root Mean Square Residual (SRMR) and Root Mean Square Error of Approximation (RMSEA). SRMR is an absolute measure of fit, estimated by the square root of the estimated discrepancy due to approximation per degree of freedom, as shown in Eq. 2 below [13]:

$$\text{SRMR} = \sqrt{\sum_{i=1}^{p}\sum_{j=1}^{i}\left[\frac{s_{ij}-\hat{\sigma}_{ij}}{s_{ii}s_{jj}}\right]^2 / p(p+1)/2} \tag{2}$$

SRMR is a badness-of-fit index, meaning larger values signal worse fit and lower value indicates better performance. Its values range from 0.0 to 1.0, with a zero indicating a perfect match whilst a value of 0.08 or less being indicative of an acceptable model [18]. SRMR is a pretty good indicator of whether the system captures the data, because it is relatively less sensitive to other issues such as violations of distributional assumptions [8].

On the other hand, RMSEA is calculated based on Eq. 3 below [29]:

$$\text{RMSEA} = \sqrt{\max(\,[((\chi^2/\mathrm{df}) - 1)/(\mathrm{N} - 1)]\,,0)} \tag{3}$$

Where

- χ^2 is the chi-square value,
- df refers to the degrees of freedom
- N is the sample size.

For a given χ^2, RMSEA decreases as sample size, N, increases. The RMSEA ranges from 0.0 to 1.0, with smaller values indicating a better model fit. A value of 0.06 or less is indicative of an acceptable model fit. RMSEA studies two types of errors - error of approximation that shows the lack of fit of the system when the parameter is optimally chosen, and the error of estimation that represents the lack of fit of the system to population data [18]. In this study, RMSEA was used to evaluate the accuracy of HyPeRM by comparing the recommended movies with the actual user ratings provided by the users.

Movies rating were taken as average of all user rating; where recommended movies with no rating, the chi square value of the particular movie user will increase. This eventually leads to higher RMSEA value and decreases the significant of the recommended movie.

RMSEA and SRMR have been used in many other studies [48, 49, 50, 51].

4.0 RESULTS AND DISCUSSION

The evaluations were administered based on two scenarios, that is, with and without user's personality. In other words, two models were evaluated, namely, the baseline model (i.e. CF-CB-DF) and HypeRM (CF-CB-DF-Personality). All the results were evaluated based on the top 10 recommendations.

Table 1 SRMR and RMSEA results

	SRMR	RMSEA
Baseline*	0.778	0.965
HyPeRM	0.532	0.773

*Baseline – CF-CB-DF

Looking at the results presented in Table 1, it can be concluded that a better accuracy is achieved when users' personalities are taken into consideration. This can be observed from the lower values of SRMR and RMSEA for HyPeRM compared to the baseline model. Fig. 6 further illustrates this point, in which point B refers to HyPeRM, point C refers to the baseline model and point A acts as the origin coordinate (i.e. (0,0)), indicating an absolute accuracy. Basically, as the RMSEA for HYPeRM is closer to point zero, it shows a higher accuracy compared to the baseline model (i.e. an improvement of approximately 19%). Similar observation can be noted for SRMR (i.e. an improvement of approximately 11%).

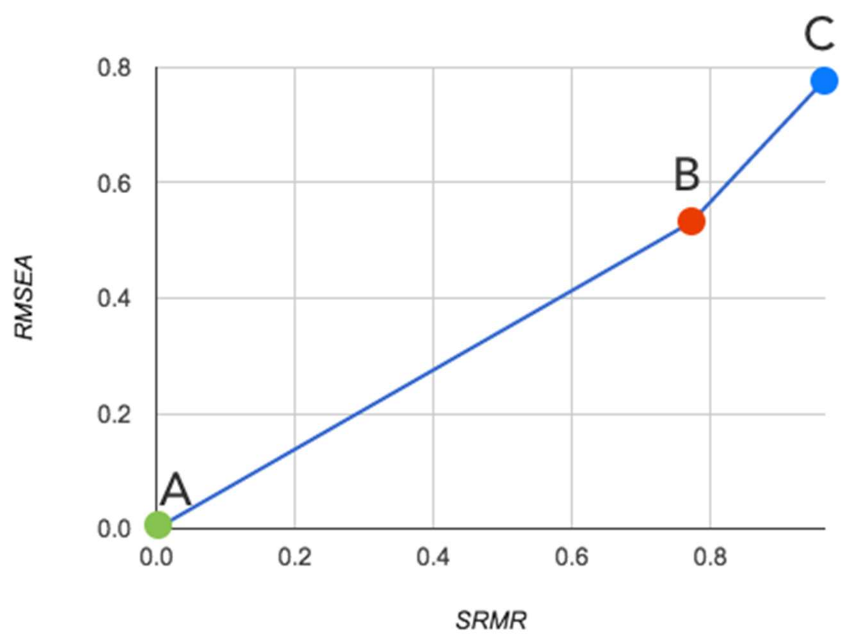

Fig. 6 Recommendation Performance Evaluation

Both the results based on RMSEA and SRMR show that movie recommendations are deemed to be more accurate when users' personalities are taken into consideration, along with their demographic details. This echoes similar studies that have showed users' personality traits to play significant roles in determining their interests [27, 21, 24, 14]. For instance, Nunes and Cerri [27] stored users' personality traits to deduce more interesting recommendations for users in order to offer them products/services as a consequence of a prediction of their future needs and behavior. The recommendation is also used as an instrument for the knowledge management service in order to predict the user behaviors and/or needs using it as those relevant information to be used during the decision making process [27].

The study clearly showed that recommendations can be further improved when several filtering techniques are integrated, that is, CF-CB-DF and personality. As users' personality traits have been shown to improve the recommendation accuracies, other recommendation systems should tap into this factor in order to provide more improvised service or experience to the users. Nevertheless, we also note several limitations to the current study. For instance, the system was tested by a small sample of users who have good technical knowledge in using search engines and recommendation systems. Perhaps future studies could look into testing similar approach with bigger sample of users, comprising of people with various skill and literacy levels.

Additionally, HyPeRM can be further extended to support other user behaviours or traits, such as emotion or aura. For instance, Ferwerda and Schedl [28] conducted a research on obtaining more personalized information such as user's state of emotion through social media to provide a better recommendation, with results showing a great improvement when the system obtains the user's state of emotion before recommending the items or service. Therefore, it would be interesting to investigate if HyPeRM can perform better when such traits are incorporated into it.

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Appendix A

Disagree Strongly	Disagree	Neither Agree nor Disagree	Agree	Agree Strongly
1	2	3	4	5

I see myself as someone who...

	1. Is talkative		23. Tends to be lazy
	2. Tends to find fault with others		24. Is emotionally stable, not easily upset
	3. Does a thorough job		25. Is inventive
	4. Is depressed, blue		26. Has an assertive personality
	5. Is original, comes up with new ideas		27. Can be cold and aloof
	6. Is reserved		28. Perseveres until the task is finished
	7. Is helpful and unselfish with others		29. Can be moody
	8. Can be somewhat careless		30. Values artistic, aesthetic experiences
	9. Is relaxed, handles stress well		31. Is sometimes shy, inhibited
	10. Is curious about many different things		32. Is considerate and kind to almost everyone
	11. Is full of energy		33. Does things efficiently
	12. Starts quarrels with others		34. Remains calm in tense situations
	13. Is a reliable worker		35. Prefers work that is routine
	14. Can be tense		36. Is outgoing, sociable
	15. Is ingenious, a deep thinker		37. Is sometimes rude to others
	16. Generates a lot of enthusiasm		38. Makes plans and follows through with them
	17. Has a forgiving nature		39. Gets nervous easily
	18. Tends to be disorganised		40. Likes to reflect, play with ideas
	19. Worries a lot		41. Has few artistic interests
	20. Has an active imagination		42. Likes to cooperate with others
	21. Tends to be quiet		43. Is easily distracted
	22. Is generally trusting		44. Is sophisticated in art, music, or literature

<u>Scoring</u>

BFI scale scoring ("R" denotes reverse-scored items; for example, if the user chooses to put agree strongly for item 21 with the score of 5, then it is reversed to the score of 1):

- Extraversion: 1, 6R, 11, 16, 21R, 26, 31R, 36
- Agreeableness: 2R, 7, 12R, 17, 22, 27R, 32, 37R, 42
- Conscientiousness: 3, 8R, 13, 18R, 23R, 28, 33, 38, 43R
- Neuroticism: 4, 9R, 14, 19, 24R, 29, 34R, 39
- Openness: 5, 10, 15, 20, 25, 30, 35R, 40, 41R, 44

**6R shows that the reverse item score is taken into consideration for item no 6. The same goes to item no with the "R" attached.*