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A hybrid personality-aware recommendation system based on personality traits and types models

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Abstract

Personality-aware recommendation systems have been proven to achieve high accuracy compared to conventional recommendation systems. In addition to that, personality-aware recommendation systems could help alleviate cold start and data sparsity problems by adding the user's personality traits in the recommendation process. The majority of the literature works used Big-Five personality model to represent the user's personality, this is due to the popularity of Big-Five model in the literature of psychology. However, from personality computing perspective, the choice of the most suitable personality model that satisfy the requirements of the recommendation application and the recommended content type still needs further investigation. In this paper, we study and compare four personality-aware recommendation systems based on different personality models, namely Big-Five traits model, Eysenck model and HEXACO model from the personality traits theory, and Myers–Briggs Type Indicator (MPTI) from the personality types theory. Furthermore, we propose a hybrid personality model for recommendation that takes advantage of the personality traits models, as well as the personality types models. Through extensive experiments on recommendation dataset, we prove the efficiency of the proposed model, especially in cold start settings. Our proposed hybrid personality-aware recommendation model improves the precision and recall in cold start settings by 21% and 18% respectively compared to the widely used Big-Five traits model.

Keywords: Personality computing, Personality-aware recommendation systems, Big-Five, FFM, recommendation systems, MPTI, HEXACO, Eysenck, Social computing.

1. Introduction

Personality Computing has emerged as a new study field that aims to capture, manipulate, and make use of the human personality character through the use of information and communication technologies. Personality computing can be viewed as the emerging domain that comes as a result of the coupling of information technologies and psychology personality theory, as shown in Figure 1. While most of the previous works in the field of personality computing have focused on Automatic Personality Recognition (APR) by analyzing the user's data (Majumder et al. 2017), and the use of personality traits to empower robots to become more social during Human-Robot interaction (Tay et al. 2014).

Recommendation systems are divided into two main categories. Collaborative filtering systems rely on the user's rating similarity with other users to deliver relevant recommendations, and it is based on the fact that users with similar ratings in the past, will have similar ratings in the future. While in content filtering, the system recommends items that are similar to the items that the user liked previously. But both content and collaborative systems face the challenge when the user is new to the system, where the system cannot determine similar items and users, a situation known as the cold start. Here comes the role of personality-aware recommendation systems (Dhelim et al. 2021a). Personality-aware recommendations were proposed as a new method that can achieve high accuracy compared to the conventional recommendation systems and alleviate the effects of cold start and data sparsity problems. Personality-aware recommendation systems have been proven as effective recommendation methods in many recommendation domains, such as product recommendation, user-interest mining, and friend recommendations. That is because personality-aware recommendation systems can leverage the user's personality traits to understand the general taste of the user. While the conventional recommendation systems rely mainly on the user ratings and user profile to deliver relevant recommendations, and such information is not easy to obtain when dealing with new users in the case of collaborative filtering, and new items in the case of content filtering. However, most of the existing personality-aware recommendation systems use Big-Five personality model to represent the user's personality (also known as Five Factors Model), this is due to the popularity of Big-Five model in the literature of psychology. Out of 160 personality-aware recommendation systems recently proposed (Dhelim et al. 2021a), 155 used Big-Five personality model for recommending different content such as product, music, movies and games. However, from a personality computing perspective, the choice of the most suitable personality model that satisfies the requirements of the recommendation application and the recommended content type still needs further investigation.

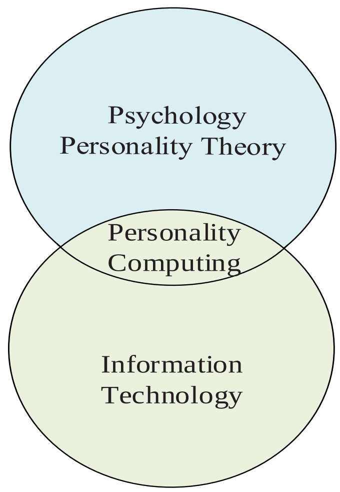

Figure 1 Personality computing scope

In this paper, we study and compare four personality-aware recommendation systems based on different personality models, namely Big-Five, Eysenck and HEXACO from the personality traits theory, and Myers–Briggs Type Indicator (MPTI) from the personality types theory. Following that, we propose a hybrid personality-aware recommendation system that takes advantage of the personality traits models, as well as the personality types models. Through extensive experiments on recommendation dataset, we prove the efficiency of the proposed model, especially in cold start settings.

The contributions of this paper are summarized as follows

- Study and compare four personality-aware recommendation systems based on Big-Five, Eysenck, HEXACO and MPTI personality models.
- Propose a hybrid personality-aware recommendation system that takes advantage of the personality traits models, as well as the personality types models.
- Perform comparative experiment by applying the proposed personality-aware recommendation systems on news recommendation dataset.

The rest of the paper is organized as follows:

In Section 2, we review the related works that have used the three personality models in the context of recommendation systems. While in Section 3, we introduce the four personality models, as well as their measurement methods. In Section 4, we introduce the fundamental concept of personality-aware recommendation and how personality traits could be incorporated into the recommendation process. In Section 5, we show the details of the conducted experiment and the evaluation process and discuss the obtained results, and finally, the paper is concluded in Section 6.

2. Related work

Personality traits have been used to improve recommendation systems in many domains, and many researchers have advocated for the massive adaptation of the user's personality characteristics and other social features in recommendation systems. Vinciarelli et al. (Vinciarelli and Mohammadi 2014) surveyed the study field of personality computing and applications of user personality in computing systems. Similarly, Kaushal et al. (Kaushal and Patwardhan 2018) surveyed the recent automatic personality recognition schemes and presented the trends of each recognition technique. Dhelim et al. (Dhelim et al. 2021a) have surveyed the literature of personality-aware recommendation systems. Dhelim et al. (Dhelim et al. 2020a) used Big-Five personality traits to improve the accuracy of user interest mining. Besides recommendation systems, users' personality was incorporated as a social feature that could be used to understand the social context of the users. Similarly, Chakrabarty et al. (Chakrabarty et al. 2020) designed a personality-aware friend recommendation system named FAFinder (Friend Affinity Finder). FAFinder uses Hellinger-Bhattacharyya Distance (H-B Distance) to measure the user's Big-Five similarity and recommend friends accordingly. In reference (Dhelim et al. 2020c), a user interest mining scheme leverages the user's personality traits in the context of social signed networks. Ning et al. (Ning et al. 2019) proposed a personality-aware friend recommendation system named PersoNet that leverages Big-Five personality traits to enhance the hybrid filtering friend selection process. PersoNet outperformed the conventional rating-based hybrid filtering, and achieve acceptable precision and recall values in cold start phase as well. While the authors of reference (Dhelim et al. 2021b) proposed Meta-Interest, a personality-aware product recommendation system based on user interest mining and meta path discovery. Their proposed system detects the user's topical interest and the items associated with these interests to perform the recommendations. In other work (Dhelim et al. 2018), the authors discussed the usage of personality information in the context of smart home scenario, and in (Ning et al. 2018) the authors discussed the excessive usage of technology on psychological disorders and its effect on the user's personality. In (Dhelim et al. 2020b) the user's personality was represented as a thinking entity that is represented by a cyber entity in the cyberspace.

Many previous works in the literature have used personality traits for academic-oriented recommendation systems, such as courses recommendations, conference attendee recommendations and research paper recommendations. Xie el al (Xia et al. 2017) proposed a recommendation system of academic conference participants called SPARP (Socially-Personality-Aware-Recommendation-of-Participants). For more effective collaborations in the vision of a smart conference, the proposed recommendation approach uses a hybrid model of interpersonal relationships among academic conference participants and their personality traits. At first, the proposed system determines the social ties among the participants based on past and present social ties from the dataset with four trial-weight parameters. These weight parameters are used later in their experiment to represent various influence factors of the past as well as current social ties among participants. Following that, the system calculates the personality similarity between the conference participants based on explicit tagged-data of the personality ratings. Fahim Uddin et al (Uddin et al. 2016) Proposed a personality-aware framework to improve academic preferences for newly enrolled students. Their proposed framework makes use of the research field of talent classification and education relevance prediction, that uses stochastic probability distribution computing to help students to choose the relevant academic field. Hariadi et el (Hariadi and Nurjanah 2017) proposed a personality-aware book recommendation system that combines the user's attributes as well as his personality traits. The proposed system leverages collaborative learning classification and content filter to compute the similarity between users and form the personality neighborhood. Hill et al (Zeigler-Hill and Monica 2015) investigated the association between HEXACO personality model with preferences for certain aspects of gaming experiences. The main finding confirmed that extraversion trait is moderately associated with the socializer gaming preference and a slight association with the daredevil gaming preference. Cai et al (Cai et al. 2020) discussed the personality aspect in human-robot interaction, and concluded that robots can be empowered by human-like personality traits. Similarly, Wang et al (Wang et al. 2021) discussed personality computing in the context of hybrid human-AI environment. In the same vein, social features of IoT users such personality traits have been proven useful in service customization (Dhelim et al. 2016, 2021c). Aung et al. (Aung et al. 2020, 2021) presented a traffic optimization system that take the drivers' personality into account when computing the shortest path to their destination. Ghadimi et al. (Mehrpooya et al. 2021) investigated optimization algorithms in different systems, while Abdalzaher and Moustafa. (Abdalzaher et al. 2021)(Moustafa et al. 2021) discussed hyperparameters optimization for machine learning models. Abualigah et al. (Abualigah et al. 2021) studied optimization algorithms that can be used in various applications including personality computing. Alasadi and Tasdemir (Tasdemir and Al-Asadi 2020) gave a tutorial regarding article recommendation systems using python.

Asabere and Acakpovi introduced ROPPSA (Asabere and Acakpovi 2020), a recommendation system that provides group recommendations for tv program viewers who have similar personality traits and tie associate these personality traits with a target tv program. Qamhieh et al. (Qamhieh et al. 2020) proposed Personalized Career-path Recommender System (PCRS), a personality-aware recommendation system that offers career guidance for high school engineering students. PCRS employs N-layered fuzzy intelligence architecture that incorporates the students' academic performance, personality type, and extra-curricular skills to offer personalized career guidance.

However, all of the above-mentioned studies did not investigate the coupling of personality traits and personality type theories to design a hybrid recommendation system that takes advantage of both theories. Table I summarizes the used personality model, as well as the recommendation technique of some of the recent related works. Our proposed model is the only system that combines both personality trait models (Big-Five and HEXACO) and personality type models (MBTI and Eysenck), which enable it to represent the user's personality in a more precise way that fit various recommendation scenarios.

Table I Personality-aware recommendation systems comparison

Ref	**Personality theory**	**Recommendation technique**	**Recommended content**	**Cold start mitigation**
Personet (Ning et al. 2019)	Big-Five	Hybrid recommendation	Friends recommendation	No
MetaInterest (Dhelim et al. 2021b)	Big-Five	Content filtering	Products recommendation	Yes
InterestMining (Dhelim et al. 2020a)	Big-Five	Collaborative filtering	Web content recommendation	Yes
PCRS (Qamhieh et al. 2020)	MBTI	Fuzzy logic	Career recommendation	No
(Moscato et al. 2020)	Big-Five	Machine learning	Music recommendation	No
ROPPSA (Asabere and	Big-Five	Collaborative filtering	TV programs recommendation	No

Acakpovi 2020)				
(Jeong et al. 2020)	MBTI	Deep learning	Service recommendation	No
Proposed	Big-Five Eysenck HEXACO MBTI	Hybrid recommendation	Generic	Yes

3. Proposed models

Since the early ages of Greek philosophers, scientists have agreed on the importance of the personality study as a vital factor to understand individual behaviors and ways of thinking. There is no unified theory that explains the human personality comprehensively. Some theories explain the difference in personality to genetics, while others associate it with sociological factors. There are many personality models that have been extensively studied from a psychological perspective such as Big-Five personality traits model, MBTI, Eysenck personality model and HEXACO personality model. These personality models differ in the way they represent the human personality, some assume that the human has "types" of personality (MBTI), while others represent the personality as a spectral of personality traits (Big-Five, Eysenck and HEXACO). From a personality computing perspective, the personality traits theory such as Big-Five model has been applied in most of the previous personality computing works. For the sake of readability, Table II lists all the used abbreviations and notations throughout the paper.

Table II Abbreviations and notations

Abbreviation	**Meaning**
Big-Five	Five factors personality model
MBTI	Myers–Briggs Type Indicator personality model
HEXACO	The six traits personality model
APR	Automatic personality recognition
$SimP(u, v)$	Personality similarity between user u and user v
$SimR(u, v)$	Rating similarity between user u and user v
$Sim(u, v)$	The overall similarity between user u and user v
α	the cold-start parameter
$\overline{r_u}$	the average rating of user u
$r_{u,i}$	the rating given by user u to item i
Ω_u	the neighbors of user u

3.1. Big-Five model

The Big-Five personality traits model (Goldberg 1990), also famous as five-factor model (FFM) is the most used model in psychology as well as personality computing works. The Big Five model mainly defines the five factors as Openness to experience, Extraversion, Conscientiousness, Agreeableness and Neuroticism. And often these traits are abbreviated as CANOE or OCEAN, as shown in Figure 2. Some of the related characters also known as facets of the Big Five personality traits are listed in Table III.

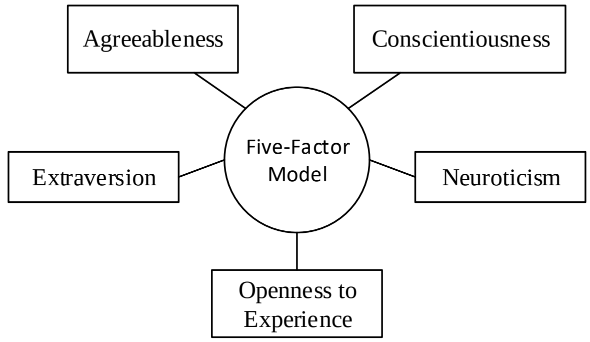

Figure 2 Big Five personality traits

Table III Big Five Traits and their associated personality facets

Personality Trait	Related Characters
Openness	Insightful, Curious, Wide interests, Imaginative, Artistic, Original
Agreeableness	Kind, Trusting, Generous, Appreciative, Forgiving, Sympathetic
Conscientiousness	Reliable, Efficient, Planful, Responsible, Thorough, Organized
Extraversion	Energetic, Assertive, Outgoing, Talkative, Active
Neuroticism	Tense, Anxious, Unstable, Touchy, Worrying, Self-pitying

3.2.Eysenck personality model

As its name indicates, this theory was proposed by Hans Eysenck (Revelle 2016). Eysenck theory is mainly based on genetics and physiology, however, he also stressed that personality could also be shaped by sociological factors. Eysenck theory assumes that the human personality could be identified by measuring three independent dimensions of temperament, mainly Neuroticism/Stability (N), Extraversion/Introversion (E), and Psychoticism/Socialisation (P) as shown in Figure 3. The characters related to each personality dimension are listed in Table VI

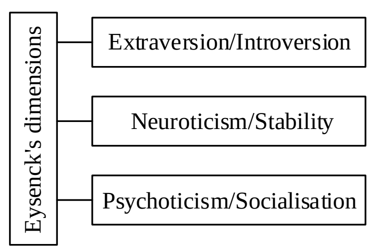

Figure 3 Eysenck personality dimensions

Table VI Eysenck dimensions and Associated Characters

Psychoticism	**Extraversion**	**Neuroticism**
Masculine	Impulsive	Tense
Dogmatic	Irresponsible	Depressed
Egocentric	Dominant	Hypochondriac
Tough-minded	Expressive	Low self-esteem
Manipulative	Sensation-seeking	Anxious
Achievement-oriented	Sociable	Obsessive
Assertive	Risk-taking	Guilt Feelings
Aggressive	Lack of reflection	Lack of autonomy
Unsympathetic	Active	Moody

3.3.HEXACO personality model

The HEXACO personality model is an extension of the Big-Five model. However HEXACO model add a new dimension known as the Honesty-Humility dimension to the other five personality traits of Big-Five model. HEXACO was proposed by Ashton and Lee (Ashton and Lee 2007). Figure 4 shows the dimensions of HEXACO model and the characters associated with each dimension are presented in Table V.

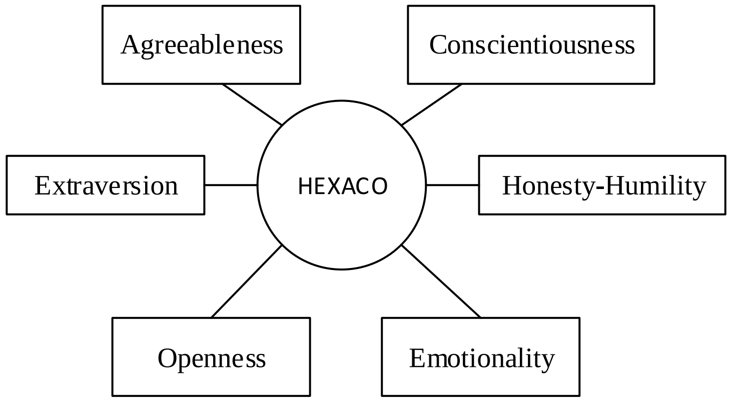

Figure 4 HEXACO personality traits

Table V Eysenck dimensions and Associated Characters

HEXACO dimension	**Associate characters**
Honesty-Humility	Greed Avoidance, Sincerity, Modesty, Fairness
Emotionality	Fearfulness, Dependence, Sentimentality, Anxiety
Extraversion	Sociability, Social Boldness, Liveliness, Social Self-Esteem,
Agreeableness	Flexibility, Forgivingness, Patience, Gentleness,
Conscientiousness	Organization, Perfectionism, Prudence, Diligence
Openness	Creativity, Aesthetic Appreciation, Unconventionality, Inquisitiveness

3.4. Myers Briggs Type Indicator

Another personality model rarely used in personality computing is the Myers Briggs Type Indicator (MBTI) (Boyle 1995), unlike HEXACO and Big-Five, MBTI defines the personality as types rather than traits, in other words, the human personality is exclusively defined by one personality type/class, rather than having a different score in multiple traits. MBTI defines 4 categories: intuition or sensing, feeling or thinking, extraversion or introversion, perceiving or judging. One letter from each category is taken to produce four-letter personality types, which makes 16 possible personality types: ISFJ, INFP, INFJ, ISTP, ISTJ, ISFP, INTP, INTJ, ENTP, ESFP, ENFP, ESFJ, ESTP, ESTJ, ENFJ and ENTJ.

3.5. Personality measurement

There are various personality measurement mediums; the most used personality measurement medium is by questionnaires, where the taker answers a set of questions with Likert scale answers about how they identify/describe themselves. There are different personality tests with various sizes (item number). The NEO-Personality-Inventory Revised (NEO-PI-R, 240 items) is a widely used personality test (Costa Jr and McCrae 2008). The NEO Five-Factor Inventory (NEO-FFI, 60 items) and the Big Five Inventory (BFI, 44 items) are also used frequently (John et al. 1991). However, in some circumstances, filling long questionnaire is not convenient, here comes the usefulness of short questionnaires, which are much faster to fill (5-10 items), BFI-10 (Rammstedt and John 2007) and TIPI (Romero et al. 2012), short tests keeps only the most strong relevant items to every personality trait. Table VI shows the items of BFI-10 Big-Five questionnaire.

Table VI The BFI-10 Personality questionnaire

Item	Question	Dimension
1	I am outgoing, sociable	Extraversion
2	I get nervous easily	Neuroticism
3	I tend to be lazy	Conscientiousness
4	I have an active imagination	Openness
5	I am reserved	Extraversion
6	I am generally trusting	Agreeableness
7	I have few artistic interests	Openness
8	I do a thorough job	Conscientiousness
9	I tend to find fault with others	Agreeableness
10	I am relaxed, handle stress well	Neuroticism

3.6. Research methodology

Our main objective in this study is to investigate the effectiveness of personality-aware recommendation systems based on different personality models.

- We study and compare recommendation systems based on four personality models, Big-Five, Eysenck and HEXACO from the personality traits theory, and Myers–Briggs Type Indicator (MPTI) from the personality types theory.
- During our comparison, we used Pearson correlation coefficient to measure the personality similarity between users, and collaborative filtering recommendation model.
- The four systems were evaluated using Newsfullness news datasets (Dhelim et al. 2020a).
- After preprocessing the dataset, we end up with the data of 1229 users, who have viewed 33450 articles for the period of 3 months.
- All the experiments have been conducted on a virtual private server with 10th Generation Intel Core i7-1065G7 Processor (8MB Cache, up to 3.9 GHz), and 16GB ram (2x8GB, DDR4, 2666MHz), running Ubuntu 19.04 operating system.

4. Personality-aware recommendation

Personality neighborhood filtering is the most common personality-aware recommendation technique. Typically, the system uses a proximity function that measures the personality similarity to find the personality neighborhood users, and use it to predict future rating accordingly. The system design of the proposed personality-aware recommendation systems is illustrated in Figure 5. The first step is the personality measurement, where the system extracts the user's personality information, either by asking the user to answer a personality questionnaire or by applying an automatic personality recognition (APR) scheme (Mehta et al. 2019). The second step is the personality similarity measurement, in which the system tries to associate the newly joined user with the most similar neighbors in terms of personality types. This step enables the personality-aware recommendation system to offer recommendations based only on personality information, which mitigates the cold-start problem (Lika et al. 2014). When the user starts to give ratings and passes the cold-start phase, the recommendation system refines the set of neighbors by incorporating the user rating in the overall similarity measurement.

There are many similarity measurement methods that can be used to measure the proximity between two users, Pearson correlation coefficient is the most commonly used proximity function. Given two users u_x and u_y, the rating similarity between them is computed using the function $SimR(u_x, u_y)$ as shown in (1), where R_x and R_y is the sets of previous ratings of user u_x and u_y respectively, and $r_{x,i}$ is the rating of user u_x on item i, and $\overline{r_x}$ is the mean rating of user u_x.

$$SimR(u_x, u_y) = \frac{\sum_{i \in R_x \cap R_y} (r_{x,i} - \overline{r_x})(r_{y,i} - \overline{r_y})}{\sqrt{\sum_{i \in R_x \cap R_y} (r_{x,i} - \overline{r_x})^2 \sum_{i \in R_x \cap R_y} (r_{y,i} - \overline{r_y})^2}} \quad (1)$$

We adopt Pearson correlation coefficient to measure the personality similarity between users, as shown in (2), where $\overline{p_x}$ and $\overline{p_y}$ is the mean value of the vector the contain the personality traits for user u_x and u_y respectively, and p_x^i is the i^{th} trait in the personality traits vector. To compare the three studied personality models (Big-five, Eysenck and HEXACO), we implement three recommendation systems by changing the personality similarity function SimP to measure the similarity of users using their respective personality models.

$$SimP(u_x, u_y) = \frac{\sum_i (p_x^i - \overline{p_x})(p_y^i - \overline{p_y})}{\sqrt{\sum_i (p_x^i - \overline{p_x})^2 \sum_i (p_y^i - \overline{p_y})^2}} \quad (2)$$

The overall similarity measurement between users u_x and u_y is computed using the function Sim, as shown in (3)

$$Sim(u_x, u_y) = \alpha \times SimP(u_x, u_y) + (1 - \alpha) \times SimR(u_x, u_y) \quad (3)$$

where α is the cold-start parameter that adjusts the portion of personality-based similarity to the total similarity measurement ($1 \geq \alpha \geq 0$), and it is negatively correlated with the number of neighbors. After computing the similarity among users and eventually establishing the personality neighborhood of each user, the prediction score is computed by aggregating the rating of neighborhood users and the similarity with these users. Formally, let $score(u, i)$ denote the prediction score that user u will give to item i, the prediction score is computed as shown in (4).

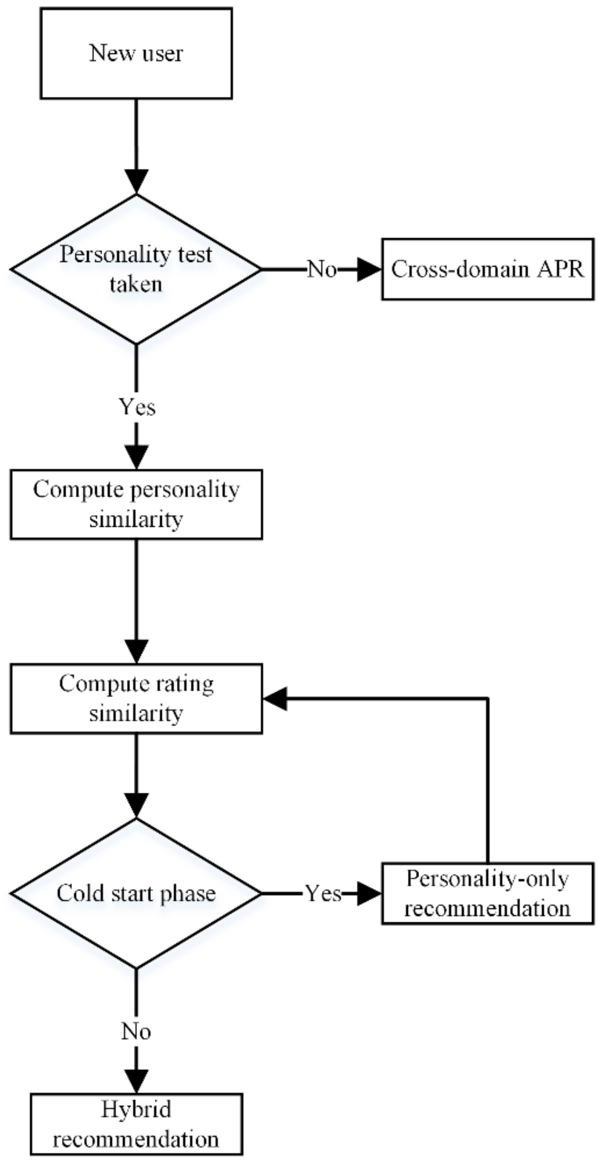

Figure 5 Personality-aware recommendation steps

$$score(u,i) = \overline{r_u} + k \sum_{v \in \Omega_u} sim(u,v)\,(r_{v,i} - \overline{r_v}) \tag{4}$$

where $\overline{r_u}$ and $\overline{r_v}$ are the average rating of user u and user v respectively, and $r_{v,i}$ is the rating given by user v to item i, and Ω_u are the neighbors of user u that have previously rated item i. The total similarity $sim(u,v)$ is the product of the rating similarity and personality similarity.

The above-mentioned personality-aware recommendation model is applied to compare the four personality models. For our proposed hybrid personality-aware recommendation system that combines the personality traits theory and the personality type theory, we extend the models as shown in Algorithm 1, where λ is the personality similarity threshold and δ is the overall similarity threshold, while MPTI(u_x) is a function that returns the MPTI personality type of user u_x, and N_x is the set of neighbors.

Algorithm 1: Hybrid_Personality_Recommender(u_x)

IF(COLDSTART) THEN
    FOREACH $u_y \in U$ Do
    IF ($SimP(u_x, u_y) > \lambda$) OR (MPTI(u_x)=MPTI(u_y))THEN
    $N_x \leftarrow N_x \cup \{u_y\}$
    ENDIF
    ENDFOR
ELSE
    FOREACH $u_y \in U$ Do
    IF ($Sim(u_x, u_y) > \delta$) AND (MPTI(u_x)=MPTI(u_y))THEN
    $N_x \leftarrow N_x \cup \{u_y\}$
    ENDIF
    ENDFOR
ENDIF

5.Experiment and evaluation

To compare the three personality models (Big-Five, Eysenck and HEXACO), we have implemented three personality-aware recommendation systems based on these personality models.

5.1. Evaluation dataset

The four systems were evaluated using Newsfullness news datasets (Dhelim et al. 2020a). The dataset contains the personality information of users that was obtained during the users' registration, and the articles viewing history of each user along with the labels related to each article. After the preprocessing step, in which we remove the passive users that have very few viewed articles, we have also removed the outliers from the list of articles that have not been viewed by any users. Finally, we have end up with the data of 1229 users, who have viewed 33450 articles for the period of 3 months. All the experiments have been conducted on a virtual private server with 10th Generation Intel Core i7-1065G7 Processor (8MB Cache, up to 3.9 GHz), and 16GB ram (2x8GB, DDR4, 2666MHz), running Ubuntu 19.04 operating system.

5.2. Evaluation metrics

After computing the personality similarity using the four personality model (Big-Five, Eysenck, HEXACO and MPTI), each personality-aware recommendation system computes the set of neighbors and recommend the relevant items accordingly. The four personality-aware recommendation systems were tested based on their precision that measures the ability of the recommendation system to compute all the relevant articles, recall that measure the ability of the correctness of the recommended items and f-measure as a measure that represents the combination of precision and recall. Specifically, we use the three studied personality-aware recommendation systems to compute the articles that are relevant to each user. Formally, Let $F = R \cup I$ be the set of all articles that were displayed to user u, where $R = \{z_1, z_2, \dots, z_r\}$ is the set relevant articles, and $I = \{z_1, z_2, \dots, z_i\}$ is the set of irrelevant articles. Let $V = \{z_1, z_2, \dots, z_v\}$ be the set of viewed articles. At this point, we want to measure the following values: (1) true positives: the set of relevant articles that the user has viewed $TP = \{x \,/\, x \in R \cap V\}$, (2) false positives: the set of irrelevant articles that viewed by the user $FP = \{x \,/\, x \in I \cap V\}$ and (3) false negatives: the group of relevant articles that not yet viewed by the user $FN = \{x \,/\, x \in R, x \notin V\}$. Based on that we have computed the precision, recall and F-measure:

Precision: the portion of relevant viewed articles in the total viewed articles, and it is computed using (5)

$$Precision = \frac{TP}{TP+FP} \qquad (5)$$

Recall: the set of relevant viewed articles in the total relevant articles, and it is computed using (6)

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

F-measure: also known as F-Score, it is the harmonic average of the recall and precision, it can be calculated using (7)

$$F = \frac{2\,P\,R}{P+R} \quad (7)$$

5.3. Results and analysis

The users classification according to the users' dominant personality traits according to Big-five, HEXACO, Eysenck and MPTI models are presented in Figure 5, Figure 6, Figure 7 and Figure 8. We can observe a similar classification for the personality type model MPTI, as the types the incorporate extraversion dimension are more populated than opposite types (types that start with I). Figure 5, Figure 6, Figure 7 and Figure 8 respectively.

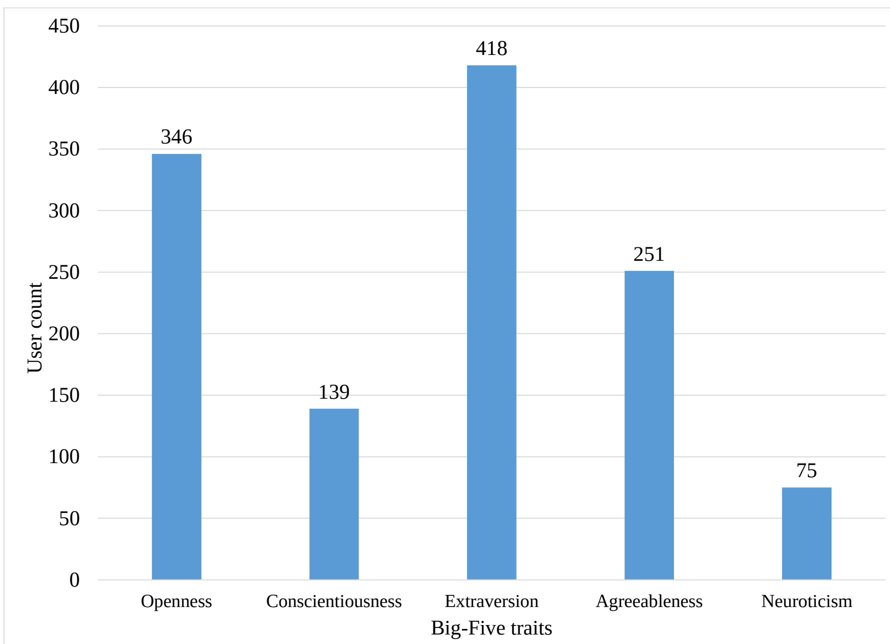

Figure 5 Big-five users classification

As we can observe the extraversion trait is the most dominant trait, and neuroticism is the least common traits among all users for all in all three personality trait models. Figure 5 shows that extraversion is the most dominant trait in Big-five model with more than 418 users, followed by openness to experience trait with 346 users and agreeableness with 251 users, conscientiousness trait with 139 and lastly Neuroticism with only 75. Similarly in Figure 6, we observe similar users classification (E=389, O=281, A=251, C=124, N=75), and the additional Honestly trait was the dominant trait in 109 users.

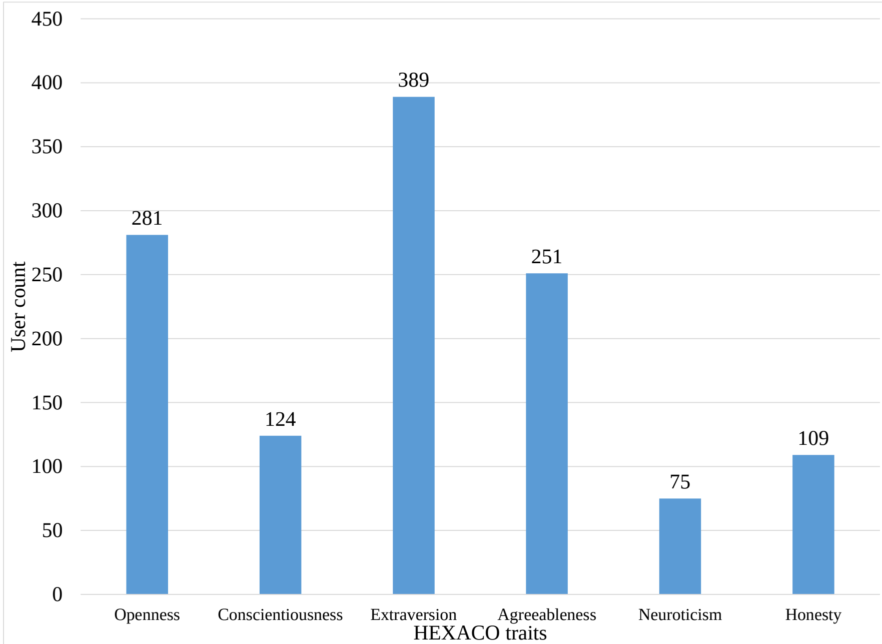

Figure 6 HEXACO users classification

Figure 7 shows the users classification according to their dominant Eysenck personality trait. Extraversion is most dominant traits among the users, followed by psychoticism trait with 461 users and Neuroticism with only 79 users. The users classification according to MPTI personality types is presented in Figure 8, as observed in personality trait models, the 8 personality types that incorporate the extraversion personality types (ESTP, ESFP, ENFP, ESTJ, ESFJ, ENFJ and ENTJ) have more users than the 8 personality types with introversion personality type (ISTJ, ISFJ, INFJ, INTJ, ISTP, ISFP, INFP and INTP). Among the 16 personality types

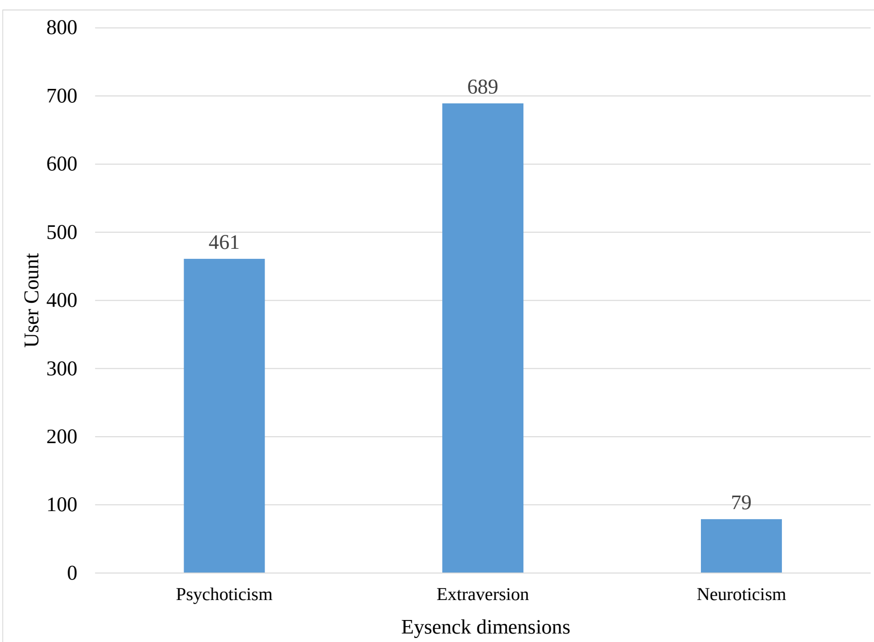

Figure 7 Eysenck users classification

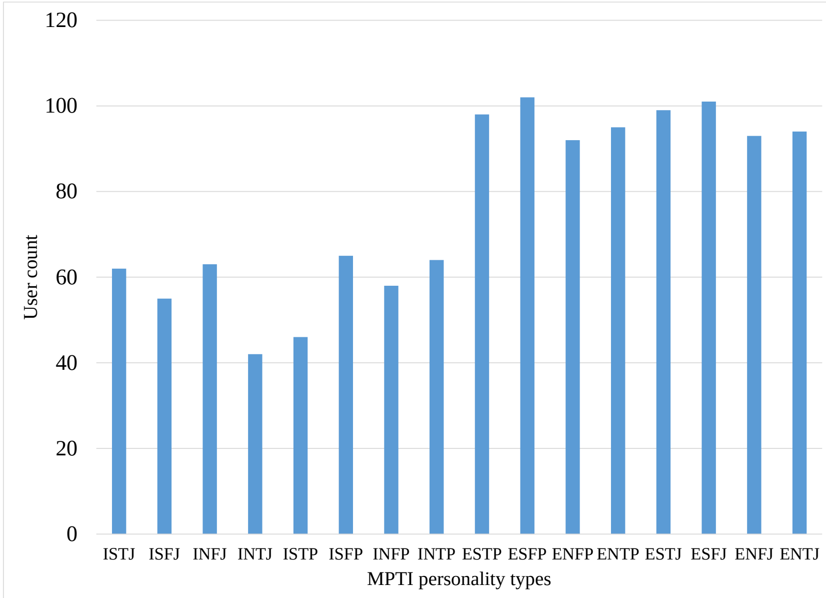

Figure 8 MPTI users classification

The performance of the three personality-aware recommendation systems in terms of precision, recall and F-measure is presented in Figure 9, Figure 10 and Figure 11 respectively. Figure 9 shows the average precision value with different values for the previously view articles count. Figure 10 shows the average recall value with different values for the previously view articles count, while Figure 11 shows the average F-Measure value with different values for the previously view articles count.

In Figure 9, we can observe that Eysenck model has a better precision value with few viewed articles count in the cold start phase compared to other personality traits models (Big-Five and HEXACO). That is because Eysenck model has only three traits, which makes categorizing users more generic. We can also notice that MPTI also performs better than (Big-Five and HEXACO), that is because MPTI is a personality type theory rather than personality trait theory, therefore it is relatively easier to find similar users with the same personality type than computing similarity with a spectrum of traits. However, when the users pass the cold start phase and view enough articles, the similarity computed with personality traits (Big-Five and HEXACO) are more accurate in computing similarities among users. Overall, our proposed hybrid model improves precision in cold start settings by 21% compared to the widely used Big-Five personality model.

From Figure 10, we can also observe that our proposed hybrid personality model has the best performance, that is because it leverages the advantages of personality type model at the cold start phase, and also the advantages of personality traits theory at later stages. Among the personality traits models, we can observe that HEXACO slightly outperforms Big-Five due to the additional sixth trait (Honesty-Humility), which can be explained that users with dominant H trait were inaccurately classified as in other five traits in Big-five.

Similarly, Figure 10 shows that Hybrid, Eysenck and MPTI also have a better recall in the cold start phase, and personality traits (Big-Five and HEXACO) have the upper hand in normal settings where the system had collected enough ratings for the studied user. However, they proposed hybrid personality model still performs better during cold start phase, as well as normal settings. The superiority of the proposed model is due to its ability to take advantage of the personality type model, hence mitigating the effect of cold start, and also leverage the accuracy in neighbor formation of the personality trait models.

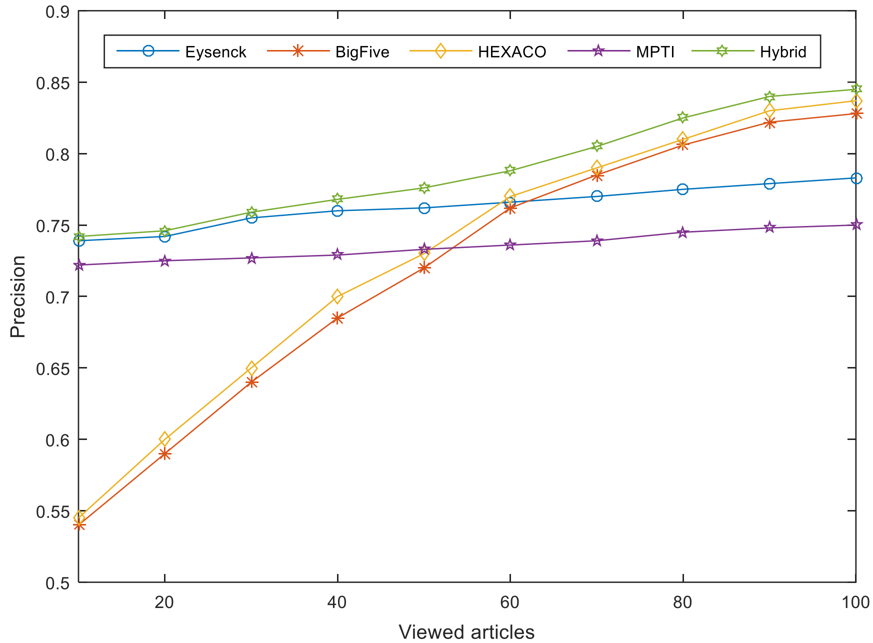

Figure 9 Precision vs viewed article count

Figure 11 shows the F-measure values that combine both the precision and recall. As an overall performance, we observe that personality type models have a higher F value in cold start settings (0-40 articles). However, as the users pass the cold start phase and enter the normal settings (more than 50 articles) the personality traits models (Big-five and HEXACO) have higher F values. Moreover, the proposed hybrid personality model has the highest F value in all settings.

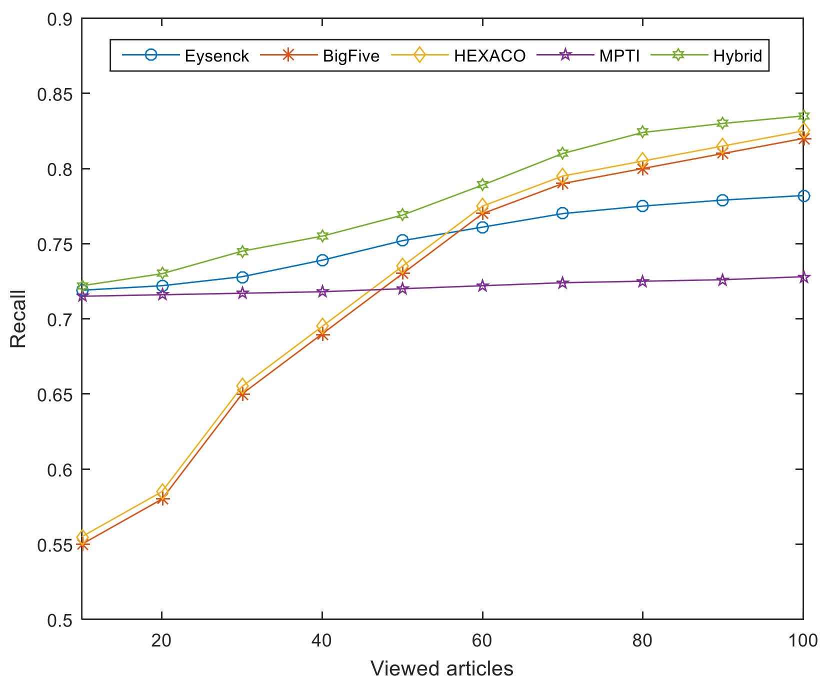

Figure 10 Recall vs viewed article count

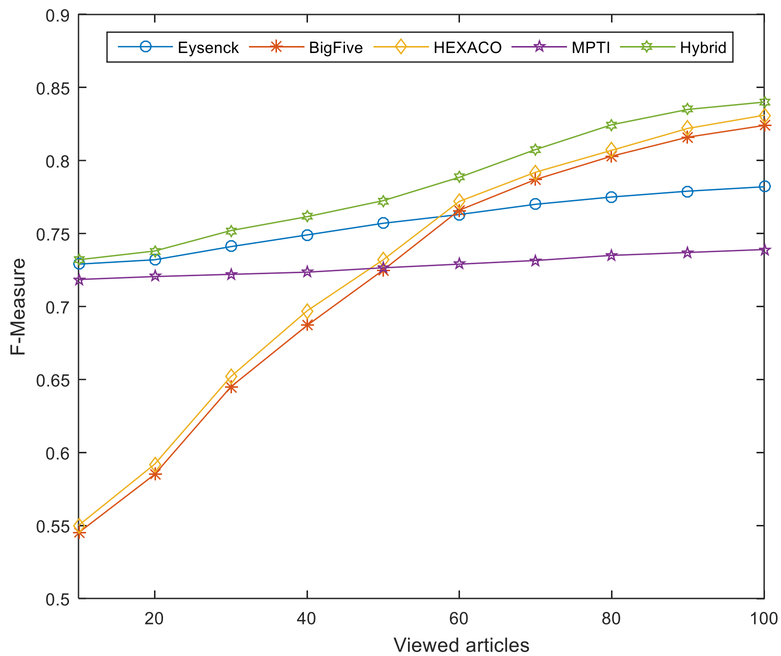

Figure 11 F-Measure vs viewed article count

6. Conclusion

In this paper, we have studied and compared four personality models (Big-Five, Eysenck, MPTI and HEXACO) in the context of recommendation systems. Moreover, we have proposed a new hybrid personality model for recommendation systems that takes advantage of the personality traits models, as well as the personality types models. The obtained results confirm that our proposed model is well suited for personality-aware recommendation systems, as it leverages the personality type model to mitigate the cold start problem, and also incorporates the advantages of the personality traits model. Eysenck model is well suited to alleviate the cold start effects more than the personality traits models (Big-Five and HEXACO). However, when the users pass the cold start phase and view enough articles, the similarity computed with personality traits (Big-Five and HEXACO) are more accurate in computing similarities among users. The results also show that HEXACO slightly outperforms Big-Five due to the additional sixth trait (Honesty-Humility).

There are many aspects in the proposed system that can be further investigated:

- In the proposed personality-aware recommendation system, a combination of personality traits and personality types models were used to represent the personality all the users. The proposed model can be further extended to offer personalized personality modeling based on the user behaviors, in such a way some users are profiled according to personality traits model, while others are modeled according to personality type model.
- The users' personality information was measured through TIPI questionnaire, integrating an automatic personality recognition scheme that leverages cross-domain data to compute the personality information is one of our future directions.

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Data availability statement: Newsfullness dataset is available for researchers by contacting the creator [8], the requester must be affiliated with research institute (e.g. university/research center), and institutional email must be used to request the dataset.